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Impacts of Weather Variations on Energy Consumption Efforts at U.S. Air Force Installations

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IMPACT OF WEATHER VARIATIONS ON ENERGY CONSUMPTION EFFORTS AT U.S. AIR FORCE BASES

THESIS

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AFIT/GEM/ENV/08-M08

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Abstract

Energy consumption is a national concern, as evidenced by federal laws aimed toward facility energy conservation measures for federal organizations. Factors, primarily weather variables, that significantly impact energy consumption must be addressed and understood to align resources and programs to meet federal energy reduction goals. An energy model was created and tested to produce an appropriate forecasting tool for energy consumption. Energy demand at Air Force installations primarily depends on climatic conditions, with a small portion attributed to a base load of non-climatic conditions, such as interior lighting and appliance loads. By gathering all energy consumption and meteorological data covering 22 years for 74 Air Force installations throughout the world, an overarching predictive model was created. Specifically, heating degree-days, cooling degree-days, wind speed, and relative humidity data were collected and analyzed to determine the influence on energy consumption. The model showed a predictive value with adjusted R^2 above 81%. Additionally, trend analysis conducted over the 22-year period provided insight into the significant use of heating load requirements during the winter months as compared to cooling load requirements in summer months. This information should encourage energy policy makers to allocate more resources into heating system requirements than into cooling requirements, taking advantage of major opportunities to reduce energy consumption.

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Chapter I. Introduction

Energy consumption has been a national concern in the United States (U.S.) since the early 1970's. This chapter begins with a background investigation of the U.S. energy use, U.S. energy policy, energy reporting mechanisms, and weather impacts on energy consumption. Then, the problem statement, research objectives/questions, methodology, assumptions, and the significance of this study are addressed. The chapter concludes with a brief explanation of the remaining chapters.

Background

In 2003, the world consumed 421 quadrillion British Thermal Units (BTUs) of energy to support its industrial, commercial, residential, and transportation sectors. By the year 2030, this number is expected to increase to approximately 722 quadrillion BTUs, equating to an average increase of two percent per year (DOE, 2006c). As the world population continues to grow and non-Organization for Economic Cooperation and Development (OECD) nations become more developed, the demand for energy from all economic sectors will continue to escalate. Since a majority of current energy production is derived from the consumption of non-renewable fossil fuels (primarily oil, natural gas, and coal), the continual increase in energy demand is rapidly depleting non-renewable energy sources (DOE, 2006c). Consequently, government leaders in the United States are extremely concerned about the United States' reliance on fossil fuels for energy production and its potential impact on national and energy security (Bush, 2001). A review of U.S. energy use, past and present U.S. energy policy, federal energy reporting mechanisms, and weather impacts on energy consumption will be discussed in this section.

United States Energy Use

In 2006, the United States consumed approximately 24 percent of the world's fossil fuel resources, a decrease from 27 percent in 1980 (DOE, 2006c; DOE, 2006a). This decrease is attributed to the increase in overall energy demand in non-OECD nations such as China and India. Although the United States' percentage of the world's energy demand decreased, Figure 1-1 depicts the growth in energy consumption compared to production in the United States. Energy consumption is expected to continue to outpace energy production, forcing the United States to rely more heavily on imports to meet requirements (Bush, 2001).

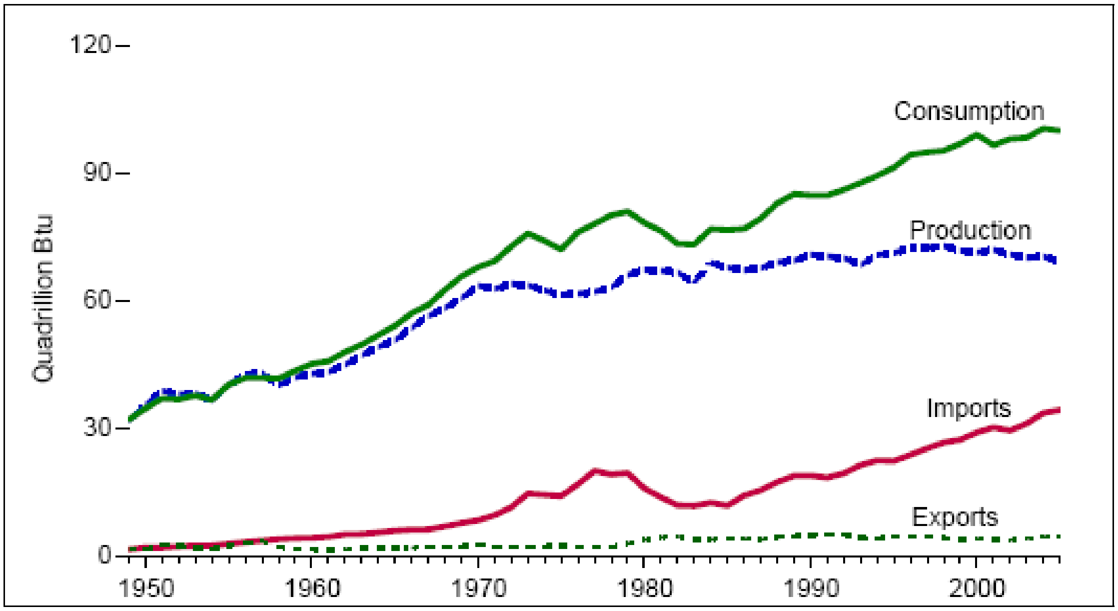

Figure 1-1. Growth in United States Energy Consumption (DOE, 2006a)

The following represents a summary of pertinent information contained in the Electric Power Annual 2006 report which indicates that electricity generation represents a significant portion of total energy consumption (DOE, 2007a). Electricity is generated from various sources: coal, petroleum, natural gas, nuclear, hydroelectric, other gases, and various renewable sources. However, a predominant amount of electricity is generated by coal. In fact, nearly 91 percent of all coal consumed in the United States in 2000 was used in the generation of electricity. In 2005, the proportion of overall coal consumed for electricity generation increased to 92 percent. In comparison to other energy sources, 55 percent of the 1,910 billion kilowatt-hours of electricity produced in 2000 came from coal. By 2005, the percentage dropped to 52.6 percent, but electrical output increased to 1,956 billion kilowatt-hours. The drop in proportion was due to a significant increase in natural gas usage and minor increases in petroleum, nuclear, and renewable energy sources. Overall electricity generation increased from 3,473 billion kilowatt-hours to 3,721 billion kilowatt-hours from 2000 to 2005 (DOE, 2007a).

Within the United States, the federal government is the single largest energy consumer in the nation, using 1,146.9 trillion BTUs of energy in 2005 (DOE, 2006a). The Department of Defense (DoD), one of many organizations within the federal government, utilized 81 percent of the federal government's total energy. Figure 1-2 displays the federal government energy usage. For the DoD, energy consumption costs for facilities alone exceed $2.5 billion annually (DoD, 2005). The extensive energy demand throughout the United States, more specifically by the federal government, stimulated interest and action in energy conservation measures and energy policy initiatives (Bush, 2001; DOE, 2006a).

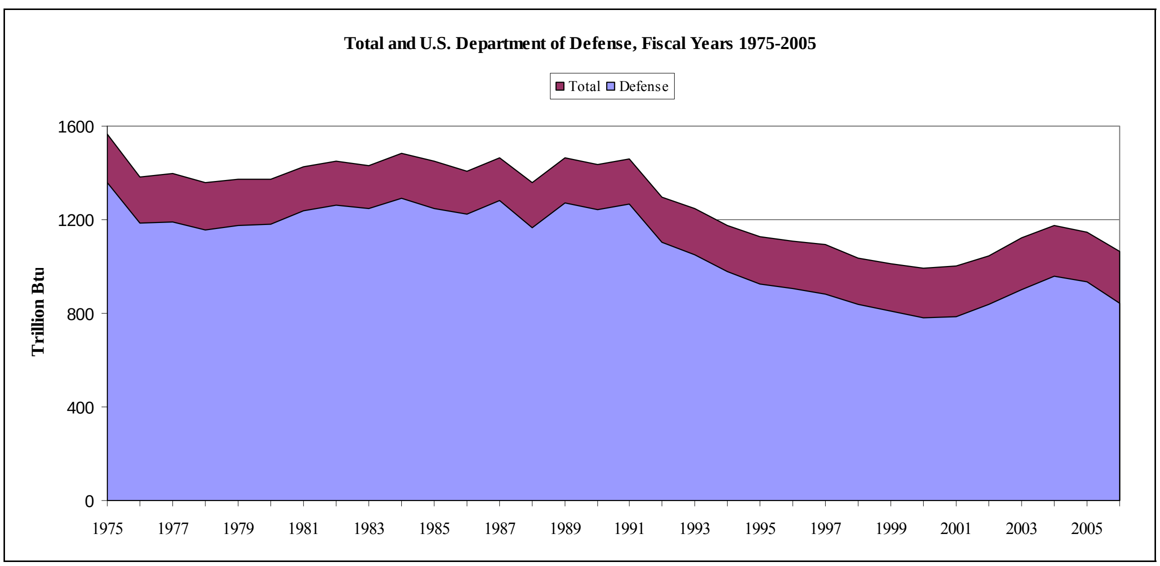

Figure 1-2. Total and U.S. Department of Defense Energy Consumption (DOE, 2006a)

United States Energy Policy

Conserving energy became a major concern in the early 1970s during a nationwide energy crisis. The 1973 oil embargo, a major factor contributing to this energy crisis, was the result of several nations in the Organization of the Petroleum Exporting Countries (OPEC) halting or reducing oil exports to the United States due to the United States' support of Israel during the Arab-Israeli war. This embargo produced gasoline shortages and significant increases in gasoline prices throughout America. The United States quickly realized the necessity of energy conservation investments to reduce the impacts of fossil fuel-driven energy markets on the economy (DOE, 2007b).

In an effort to ease the energy crisis, President Nixon crafted several energy policies aimed at reducing United States reliance on fossil fuels and promoting energy conservation initiatives. To champion the United States energy policies, the Department of Energy was created on October 1, 1977, with the charter to "provide the framework for a comprehensive and balanced national energy plan by coordinating and administering the energy functions of the federal government" (DOE, 2007c). The Energy Policy and Conservation Act of 1975 was the first energy policy created; it directed the President to develop standards for energy efficiency and a 10-year plan for energy conservation efforts in federal buildings. Later, the National Energy Conservation Policy Act of 1978 set forth a more robust national energy policy. This act stipulated the need for continued efforts toward energy efficiency throughout the economy, controls on the growth rate of demand for energy, more independence from the world oil market, and reductions in demand for non-renewable energy sources through conservation measures. It also established the first measurable energy consumption reduction goal in federal facilities that spanned a 15-year time period (from 1985 to 2000). This act paved the way for future policies and guidelines.

In addition to the National Energy Conservation Policy Act of 1978, two critical documents were created that provided significant support, flexibility, and guidance for federal agency compliance: the Energy Policy Act (EPAct) of 1992 and Executive Order 12902 of March 1994. The EPAct of 1992 provided federal organizations the authority to engage in energy savings performance contracts (ESPC) to accomplish energy conservation. The implementation of ESPCs shifted the burden of capital investments to the contractors who, in turn, benefited from the energy savings created from its endeavors. Federal organizations would then gain the energy savings benefit at the conclusion of the contractual obligations of the ESPC. Executive Order 12902 mandated a 30 percent reduction in energy consumption in each federal facility from 1995 to 2005. This energy reduction, measured in energy consumption per gross-square-foot, was to be compared to a baseline consumption year of 1985. These policies sought to promote efficient use of all fossil fuels and to continue investigating viable renewable energy sources.

In 2001, President Bush (2001) formalized five national goals: "America must modernize conservation, modernize our energy infrastructure, increase energy supplies, accelerate the protection and improvement of the environment, and increase our nation's energy security." To further improve energy conservation efforts and align policy guidance with these five national goals, the EPAct of 1992 and Executive Order 12902 were superseded by the Energy Policy Act (EPAct) of 2005 and Executive Order 13123 of June 1999, respectively. Amendments to the prior policies included continued emphasis on reduction in energy consumption and greenhouse gas emissions and increasing usage of alternative energy sources. Specifically, the EPAct of 2005 extended the energy reduction requirement for federal facilities from 2005 to 2105; it also mandated a two percent annual reduction in energy use and changed the baseline year from 1985 to 2003. Furthermore, Executive Order 13123 extended the energy conservation goals set forth in Executive Order 12902 from 2005 to 2010 and required a 35 percent reduction by 2010 from the 1985 baseline year. Executive Order 13123 was later superseded by Executive Order 13423 of January 2007, which further emphasized energy conservation by increasing the annual energy reduction to three percent through 2015. With federal legislative guidance mandating energy conservation, a reporting mechanism was needed to capture the attainment of those reduction goals.

Energy Reporting Mechanism

In February of 1974, the Defense Energy Information System (DEIS) was initiated to report energy resource usage in federal facilities. This automated management system monitors all DoD energy utility supplies and consumption data and is vital for managing the EPAct and Executive Order energy reduction goals. The DEIS was later renamed the Defense Utility Energy Reporting System (DUERS) (DoD, 1993).

The DUERS provides valuable information to energy policy makers to assist in the development and execution of DoD energy programs. DUERS data collected by Air

Force energy managers is "used by the Air Staff to budget for future energy costs, to track energy goal progress, to validate energy efficiency projects, to analyze Air Force consumption trends, and most important, to develop long-term policy that ensures adequate and deliverable energy resources are available in support of the Air Force mission" (Department of the Air Force, 1996, p.1). The data, gathered since the baseline year of Fiscal Year (FY) 1985 from all Air Force installations, is maintained at the Air Force Civil Engineer Support Agency (AFCESA). The data is then presented to the Office of the Secretary of Defense annually and used in the assessment of DoD energy policy. To be meaningful though, analysis of this data should include the impact of other related factors, with an important factor being weather.

Weather Impacts on Energy Consumption

Calculating expected energy consumption values is a complex task for individual facilities, large regions, and Air Force installations containing a wide variety of facilities. Energy consumption is influenced by numerous weather conditions including air temperature, relative humidity, and wind speed (Eto, 1988). The difficulties experienced in predicting energy consumption estimates due to these impacts have generated several research efforts (e.g., Eto, 1988; Valor, Meneu & Caselles, 2001; Sailor & Munoz, 1997; Pardo, Meneu & Valor, 2002). The most notable trend observed in the existing literature was that, of all weather conditions studied, outdoor air temperature had the most significant impact on energy consumption, thus becoming the standard measure of analysis.

Analyses of weather conditions and their effects on reported energy consumption have been accomplished involving individual facilities and entire regions or countries such as Turkey or Spain; however, research covering Air Force installations or comparably-sized areas does not appear to have been accomplished. Additionally, many of the research efforts focused on only one energy source (primarily electricity) and covered one economic sector (residential). Therefore, this research effort intended to bridge that gap in the literature and provide a more broad analysis than individual facilities, yet more focused than entire countries or regions. This research effort also covered numerous energy sources and two economic sectors.

Problem Statement

The federal government promotes a comprehensive energy policy that directs its various agencies to comply with federal laws, regulations, executive orders, and policies; these agencies are chartered to execute those legislative directives in the most effective and efficient manner. Specifically, the effectiveness of Air Force energy programs depends largely on the abilities of base energy managers to accurately assess and manage those programs through the use of energy initiatives that minimize energy consumption while maximizing energy conservation. Energy managers are also charged to "promote efficiency and reduce costs as much as possible without jeopardizing mission capabilities or reducing the quality of life for DoD personnel" (DoD, 2005, p. 2). However, the attainment of mandated energy goals are difficult to accomplish without a full understanding of weather related impacts on energy consumption. Therefore, it is vital to identify those variables that influence facility energy usage. The main research objective of this effort was to evaluate the impact of weather variations on energy consumption efforts at Air Force installations located throughout the world.

Research Objectives/Questions

This research effort attempted to answer the following questions in support of the research objective.

1. What type of variation does weather impose on energy consumption at Air Force bases?

2. Which months are best/worst in terms of energy consumption?

3. Which energy sources (electricity, natural gas, other) vary the greatest between the heating and cooling seasons?

This research effort also provided a user-friendly energy model to be used by energy managers to determine energy consumption rates based on various weather parameters.

Methodology

Energy consumption and weather data were statistically analyzed through multiple linear regression to create an overarching energy consumption model applicable to each U.S. Air Force installation worldwide. Based on existing literature, the three weather conditions analyzed in this thesis effort were outdoor air temperature (in the form of heating and cooling degree-days), wind speed, and relative humidity. A step-by-step process was undertaken to review existing energy and weather data and to ensure all linear regression-related assumptions were met in order to produce a statistically sound and useful energy model. Additionally, graphical statistical methods were used to conduct applicable trend analysis to determine which months are best and worst in terms of energy consumption and to identify which energy sources vary the most during the heating and cooling seasons.

Assumptions

Two assumptions were made during the course of this research work. First, the energy consumption data collected from each base were assumed to be accurate and complete, specifically total installation square footage and energy usage per fuel source. Second, the weather data were also considered accurate and complete.

Significance of Study

Appropriate implementation of base energy programs is essential to meeting U.S. energy conservation goals. This research effort could potentially provide useful information to Air Force energy policy decision-makers, headquarters-level energy managers, career field leaders, and base energy managers. Specifically, the energy model will provide insight into the relationship between energy consumption and weather, thereby providing a method to predict future weather-based energy requirements. This research effort will also add to the existing literature and cover a geographical area yet to be analyzed in detail.

Purpose of Remaining Chapters

The remainder of this thesis consists of four chapters: Literature Review, Methodology, Results, and Discussion. Chapter II presents an in-depth review of relevant literature pertaining to national energy policy and energy consumption. Chapter III provides a discussion of the methodology used to statistically analyze weather impacts on energy consumption. Chapter IV discusses the results of the data analysis. Finally, Chapter V presents the conclusions, recommendations, and suggestions for future research efforts.

Chapter II. Literature Review

This thesis effort discusses weather impacts on energy consumption; therefore, it is important to understand the weather mechanisms used in the analysis and the various energy sources consumed on Air Force installations. A review of previous efforts that identify various influencing factors is equally important to fully address all aspects related to energy consumption. Numerous energy studies have been completed that bracket the spectrum from investigations of individual buildings to those covering large regions; however, none covered the areas that fall between these two extremes, such as those involving areas comparable in size to Air Force installations. Despite these shortcomings, the existing literature contains a knowledge base of weather parameters which influences energy consumption and provides insight into which factors are the best candidates to be utilized in this thesis effort. Thus, weather parameters, heating and cooling degree-day fundamentals, and the Defense Utility Energy Reporting System (DUERS) process are discussed, followed by an explanation of energy sources utilized at Air Force installations.

Weather Parameters

As referenced in the previous chapter, existing literature shows that weather does impact energy consumption. Numerous regression analyses have indicated correlations between weather and energy consumption; the resulting models are commonly used to predict future energy demands either on individual buildings or in regional areas (Lam, 1998; Eto, 1988; Valor, Meneu & Caselles, 2001; Sailor & Munoz, 1997; Pardo, Meneu

& Valor, 2002). More specifically, weather parameters such as air temperature, relative humidity, and wind speed have been found to influence energy consumption (Eto, 1988). Furthermore, researchers are in consensus that the leading weather parameter with the most significant impact on energy usage is outdoor air temperature (Sailor, 2001; Eto, 1988; Lam, 1998; Quayle & Diaz, 1980; Valor, Meneu & Caselles, 2001).

In a study conducted by Lam (1998), energy data covering a 23-year period (1971 to 1993) were analyzed to determine the relationship between residential electricity consumption and climatic factors in Hong Kong. Lam (1998) selected cooling degree-days (CDD) (derivation of outdoor air temperature which is discussed later in this chapter), latent enthalpy days (humidity reduction requirement), and cooling radiation days (measure of cooling load due to solar radiation) as the three critical weather parameters used in his analysis. He initially performed multiple linear regression analysis with all three independent variables and later with only CDD as the independent variable. The results of the analysis indicated a strong influence of CDD, but that latent enthalpy days and cooling radiation days were not statistically significant in affecting residential energy consumption on a regional scale. He surmised that dropping latent enthalpy and cooling radiation days did not significantly affect the regression correlation and stated that CDD accounted for 74 to 93 percent of the variation in residential electricity consumption. Lam (1998) also added three social, economic, and demographic variables (household size, average monthly household income, and electricity price) to the regression equation. He analyzed the monthly and annual data, converted the numbers into their natural logarithm, and achieved coefficient of determination, R^2, values of 0.9 and 0.98, respectively. The results of this study support the claim that outdoor air temperature has a large influence on energy consumption and are valuable in the creation of an energy model.

Yan (1998) followed Lam's (1998) Hong Kong study with one that covered the time period of 1980 through 1994 and investigated the impacts of vapor pressure, cloud cover, humidity, and mean air temperature on residential electricity consumption. He gathered monthly residential electricity consumption data and average monthly mean temperatures for the analysis. He also used a "*clo"* factor, which "measures the amount of clothing insulation required to maintain comfort under given atmospheric and metabolic conditions" (Yan, 1998, p.17). This *clo* factor was calculated using various parameters including cloud cover, ambient air temperature, and dry heat transfer, which were then averaged into monthly figures. In addition to the above variables, a time factor, in terms of different years, was added to eliminate the effect economic growth had on energy consumption. Using multiple regression analysis, Yan (1998) found that vapor pressure and cloud cover were not statistically significantly related to energy consumption in the residential sector, while mean temperature did exhibit a strong relationship. Yan (1998) produced R^2 values that ranged from 0.82 to 0.902 in his analysis.

Sailor (2001) conducted an analysis that measured air temperature, wind speed, and humidity effects in another regional study that covered eight geographically diverse states located in the United States (California, Florida, Illinois, Louisiana, New York, Ohio, Texas, and Washington). Sailor (2001) obtained monthly residential and, unlike the above two studies, commercial electricity consumption data for each state covering 10 to 15 years and subsequently adjusted the data to convert it into a per capita consumption measure. Additionally, he adjusted the data to reduce the non-climate related consumption trend. Sailor (2001) used heating degree-days (HDD), CDD, humidity, and wind speed as the independent variables in his model. The results indicated that air temperature, in the form of HDD and CDD, was statistically significant in all eight states, wind speed was statistically significant in four states (Florida, Louisiana, New York, and Texas), and humidity was only statistically significant in one state (Louisiana). The resulting regression models produced R^2 values that fell between 0.709 and 0.873. As with Lam's (1998) and Yan's (1998) studies, Sailor's (2001) analysis provided confirmation that outdoor air temperature was again an important climatic variable, along with evidence for wind speed and possibly humidity as candidates.

Valor, Meneu, and Caselles (2001) conducted another regional study that analyzed the relationship between air temperature and energy consumption in Spain in an attempt to create a model that predicted future consumption needs. This study was slightly different from the three studies shown above in that it was not restricted to only residential electricity use as Yan (1998) and Lam's (1998) studies were or to residential and commercial electricity use as Sailor (2001). This study included residential, commercial, and industrial sectors throughout Spain in the analysis. They collected daily electricity loads and daily mean air temperatures from January 1983 to April 1999. The daily mean air temperatures were then population-weighted because disaggregated electricity consumption data were not available for the different regions. After this adjustment, the mean temperatures were then converted to HDD and CDD. Of special note, Valor et al. (2001) used elasticity demand functions to create their models instead of regression and only analyzed HDD and CDD climatic variables. Therefore, a direct comparison of R^2 values was not possible. Their results, however, indicated a sensitivity of electricity load to daily air temperatures. This study proved beneficial since it included industrial and commercial sector electricity data with residential data. Since Air Force installations include facilities that are included in commercial and residential economic sectors, this study provided valuable information in their overall impact.

Le Comte and Warren (1981) used national population-weighted CDD data to observe the influence of cooling season temperatures on electricity consumption in the contiguous United States. Over a three year period (1977 through 1979), daily CDD were collected and converted into weekly population-weighted CDD totals. Weekly national electricity use data from the industrial, commercial, and residential sectors were also collected for the analysis. This analysis was unique in that the regression equation included growth factors for two of the three years, a holiday factor dummy variable to indicate holiday weeks, and the previous week's national CDD totals. Le Comte and Warren (1981) included the previous week's CDD totals in the model because they felt that cooling requirements for the current week were partially derived from the previous week's heat buildup. The model produced impressive results in which the independent variables accounted for 96 percent of the national electricity consumption (i.e., $R^2 = 0.96$).

In a study that included electricity and fuel oil, Quayle and Diaz (1980) analyzed the influence of outdoor air temperatures (in the form of HDD) on energy consumption in 40,000 individual residences in a 2,500 square mile area in Asheville, North Carolina, over an 11-year period. Using monthly electricity and fuel oil consumption data, Quayle and Diaz (1980) created regression models to measure the relationships. Regarding the electricity consumption numbers, a non-climate consumption baseline was established by averaging the June through August consumption values. This was possible since Asheville experiences mild summers that do not require a significant air conditioning load. It was thus assumed that the electricity loads for those months were a sufficient baseline and were removed from the monthly electricity consumption values. Both models produced excellent results, achieving correlation coefficients over 0.90 (i.e., R = 0.90). Although the study did not include any weather parameters other than HDD, it was beneficial in that it included two energy sources in its regression analysis and provided possibilities into baseline calculations.

Finally, Mirasgedis et al. (2006) modeled daily and monthly electricity consumption values over a 10–year period (1993 to 2002) in Greece. They obtained hourly data of the electric load in all economic sectors and calculated daily and monthly values from the data. For weather parameters, mean daily outdoor temperature and mean daily relative humidity were obtained from two meteorological stations located in northern and southern Greece. Two models were created; the daily model included daily, holiday, and monthly dummy variables while the monthly model included monthly dummy variables. Both models included HDD, CDD, relative humidity measures, a time variable which approximated the long-term trend in electricity demand created by economic development in Greece, and autocorrelation variables. Additionally, the electricity consumption data was transformed by taking the natural logarithms in an attempt to eliminate heteroskedasticity. The results of the models produced R^2 values of 96 percent (daily) and 98 percent (monthly), the highest noted in all of the literature. This study provided keen insight into the use of dummy variables to help increase the accuracy of the regression models, along with the influence of heating and cooling degree-days and relative humidity.

Thus, existing literature is in agreement that outdoor air temperature provides the most significant influence on energy consumption, while other weather parameters have varying levels of impacts. In each of the studies above that included linear regression, the coefficients associated with HDD and CDD were all positive. This means that in all regression models, as heating or cooling degree-days increases, the energy consumption value increases by that coefficient amount. Of the weather factors addressed, outdoor air temperature, wind speed, and relative humidity were analyzed in this thesis effort. In order to properly analyze outdoor air temperature and its impact on energy consumption, it must be converted from its raw form into heating and cooling degree-days. Therefore, a detailed account of heating and cooling degree-day information is provided next.

Heating and Cooling Degree-day Fundamentals

Once outdoor mean air temperatures are recorded, heating and cooling degree-days can then be derived from the data. Degree-day analyses used for weather normalization are common in literature because of the availability of unbiased air temperature data and the lack of other less complicated or data intensive options (Eto, 1988). Airports, weather bureaus, and Air Force installations collect daily and, in some instances, hourly temperature data that is widely accessible, which is then converted to heating and cooling degree-days. Eto (1988) defines heating degree-days as "the sum of the positive differences between a base temperature and the average daily outdoor dry-bulb temperature for a given time period" (p. 114). Cooling degree-days are determined using a similar process. The formulas for both degree-day processes are shown below (Buyukalaca, Bulut, & Yilmaz, 2001).

$$\text{HDD} = (1day)\sum_{days}(T_b - T_m)^+ \tag{1}$$

$$\text{CDD} = (1day)\sum_{days}(T_m - T_b)^+ \tag{2}$$

where HDD equals heating degree-days, CDD equals cooling degree-days, T_b equals the base temperature, and T_m equals the daily mean outdoor temperature.

The base temperature, T_b, is commonly defined as 65 degrees Fahrenheit (18.3 degrees Celsius) (Le Comte & Warren, 1981; Lam, 1998; Eto, 1988; Valor, Meneu, & Caselles, 2001; Sailor & Munoz, 1997). The daily mean outdoor temperature is calculated using the following formula (Buyukalaca, Bulut, & Yilmaz, 2001).

$$T_m = \frac{(T_h + T_l)}{2} \tag{3}$$

where T_h and T_l equals the highest (maximum) and lowest (minimum) daily temperatures, respectively.

The heating and cooling degree-day method has numerous applications. Buyukalaca, Bulut, and Yilmaz (2001) discussed the use of the degree-day method in developing heating, ventilating, and air-conditioning (HVAC) system designs focused on efficiency and cost effectiveness and to indicate energy demand requirements to heat or cool a facility. Le Comte and Warren (1981) applied the degree-day method to model summer temperatures on national electricity consumption using population-weighted weekly degree-day totals. However, the majority of applications of the degree-day method focus on predicting regional or individual facility energy consumption estimates (Eto, 1988; Valor, Meneu & Caselles, 2001; Yan, 1998; Lam, 1998; Sailor, 2001; Mirasgedis et al., 2006; Sailor & Munoz, 1997; Pardo, Meneu & Valor, 2002; Sarak & Satman, 2003; Quayle & Diaz, 1980).

Defense Utility Energy Reporting System (DUERS) Process

As discussed in Chapter I, a reporting system was required to capture energy consumption data in order to measure energy reduction efforts in federal facilities. The Defense Energy Information System (DEIS) was created in 1974 to provide the means to account for utility energy resource consumption in Department of Defense (DoD) facilities (DoD, 1993; Department of the Air Force, 1996). This automated management system records all DoD energy utility consumption data and is vital in managing the Energy Policy Act and Executive Order energy reduction goals previously discussed in Chapter I. The Defense Utility Energy Reporting System (DUERS) superseded the DEIS reporting system and provides policy makers with energy data to enable the development and execution of federal energy programs (DoD, 1993). The energy consumption figures are integral in tracking energy goal conservation progress, corroborating energy reduction projects' performances, and monitoring overall consumption trends in support of the Air Force mission (Department of the Air Force, 1996). Each Air Force installation is required to collect and submit all energy consumption data quarterly to their respective major command (MAJCOM), who then submits the data to the Air Force Civil Engineer Support Agency (AFCESA). Annually, AFCESA submits the Air Force's total energy consumption data to the Office of the Secretary of Defense (Department of the Air Force, 1996).

Energy Source Analysis

An understanding of the predominant national energy sources and their respective uses is necessary to develop and analyze the results of the energy consumption model and to conduct trend analysis. The following sections will discuss common energy sources found in the United States and their uses throughout the various economic sectors.

Common Energy Sources

Energy is produced from fossil fuels (coal, natural gas, and crude oil), nuclear power, and renewable sources (hydroelectric, geothermal, solar/photovoltaic, wind, and biomass) (Annual Energy Review, 2006). Figure 2-1 displays the United States' energy flow beginning with the raw products and ending with the economic sectors into which it flows. These various energy sources are used to meet all energy requirements for Air Force installations. Therefore, the DUERS categorically collects consumption data from the following utility sources: electricity, natural gas, fuel oil, coal, propane/liquefied petroleum gas/butane, photovoltaic, solar thermal, wind, wood, geothermal, refuse-derived, and hydroelectric power (Department of the Air Force, 1996).

As each energy source is purchased and consumed, the British Thermal Unit (BTU) equivalent is determined and consolidated into an overall energy consumption total for the installation. The BTU amount, cost per energy source, and total BTU consumption are captured in the DUERS. Additionally, the DUERS requires energy consumption for military family housing units and commercial facilities to be recorded separately (Department of the Air Force, 1996).

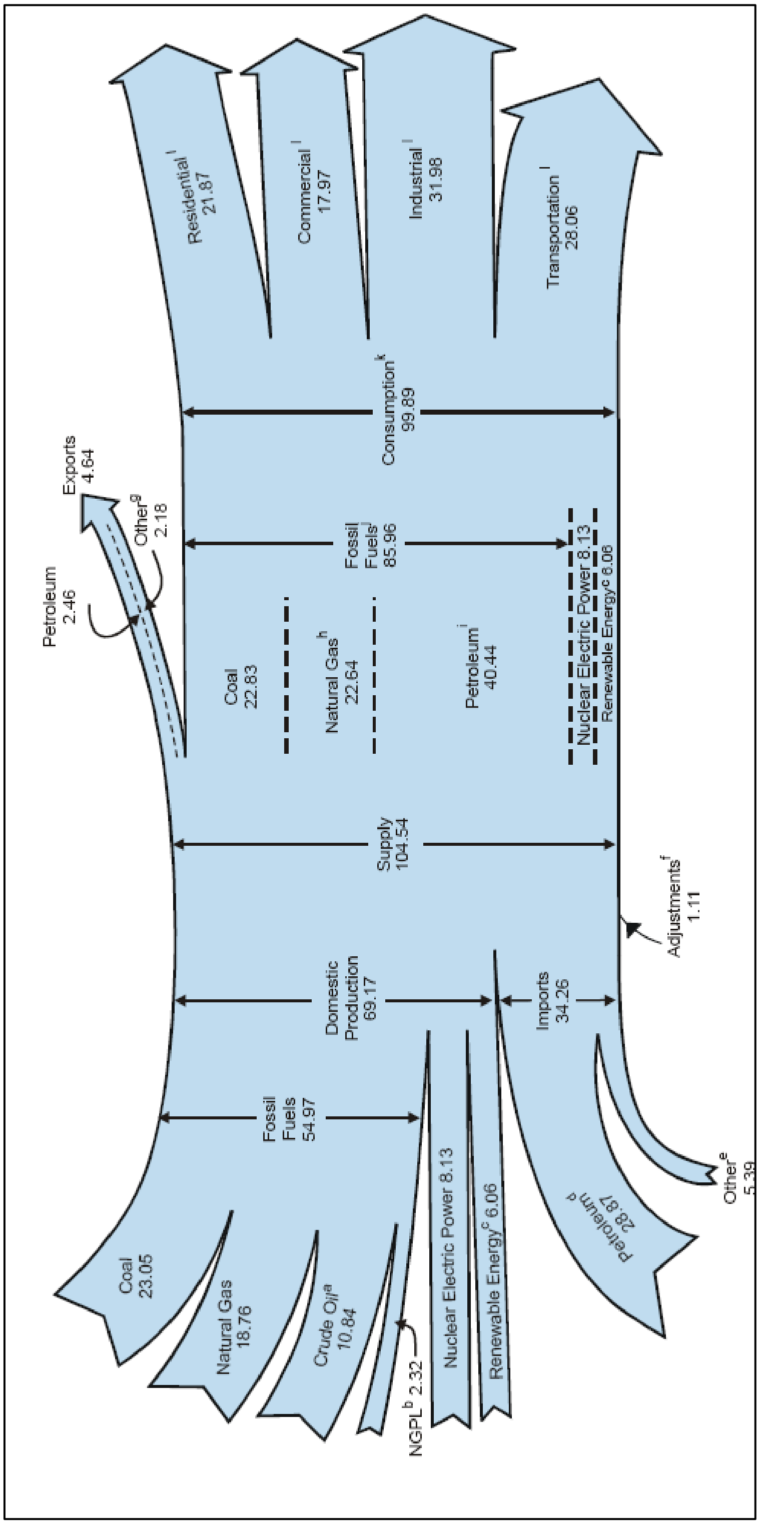

Figure 2-1. United States Energy Flow in 2005 (DOE, 2006a)

Energy Source Usage

Air Force installations are commonly divided between residential and commercial sectors. The residential sector is composed of military family housing, while the commercial sector contains offices, warehouses, hangars, and other non-housing facilities. Energy consumption for other billeting facilities (such as dormitories, temporary living facilities, and visiting officers and enlisted quarters) are combined in the commercial sector's total. Each sector has varying energy source demands and requirements. Table 2-1 displays these various energy sources and their respective consumption percentages in the residential and commercial sectors (DOE, 2006a). Recognizing and understanding the different energy requirements for each sector is critical in accurately normalizing energy consumption data using selected weather parameters. Figure 2-2 provides a view of the total Air Force facility energy source usage in 2006. Table 2-1 and Figure 2-2 provide information regarding which energy source is used in the greatest quantity on Air Force installations, thereby enabling investigation into research questions two and three identified in Chapter I.

Table 2-1. United States Residential and Commercial Sector Consumption Percentage by Energy Source (DOE, 2006a)

Energy Source	Residential	Commercial
Natural Gas	46.6 percent	37.7 percent
Electricity	37.9 percent	58.0 percent
Fuel Oil/LPG	11.7 percent	3.8 percent
Wood	3.9 percent	0.0 percent
District Heat	0.0 percent	7.5 percent

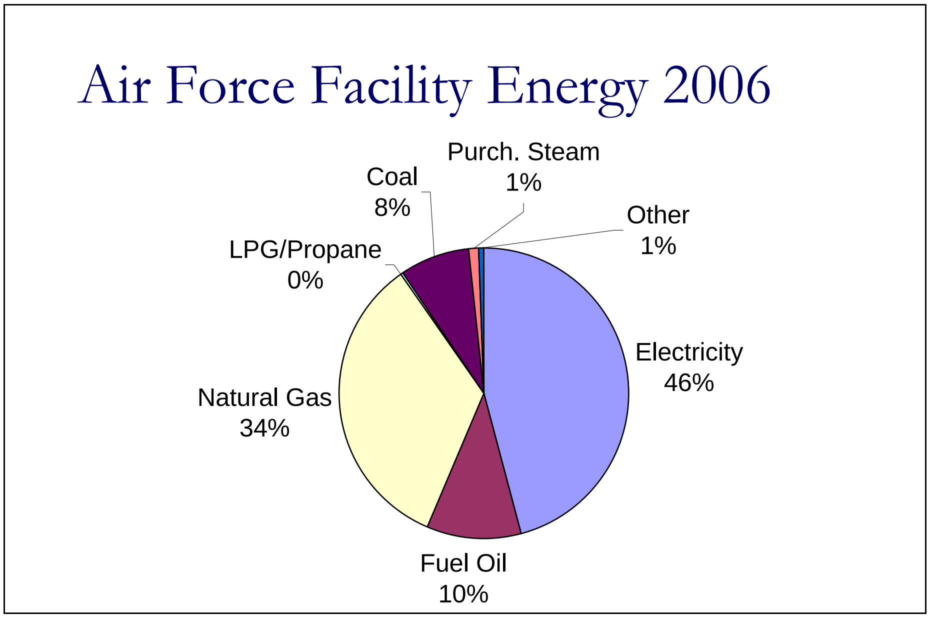

Figure 2-2. Air Force Facility Energy Data 2006 (AFCESA, personal communication, September 27, 2007)

Further distilling energy consumption data, all energy sources do not contribute equally to major energy requirements in facilities, such as heating and cooling loads or lighting. For example, natural gas is not commonly used to meet cooling requirements in buildings; however, it is most commonly used in providing space heating. Electricity, by contrast, is used for both heating and cooling requirements in addition to providing power to non-process systems such as lighting and electrical appliances. Electricity, though, is used proportionally more in cooling than heating as demonstrated in the commercial sector. Electricity used in meeting cooling demands accounts for 25.6 percent of all electricity usage in the commercial sector, while only 5 percent of electricity satisfies space heating needs (DOE, 2006a).

Renewable energy sources such as solar/photovoltaic, wind, and hydroelectric are also used to generate electricity. Other renewable energy sources are used to support heating requirements, like biomass and geothermal (DOE, 2006a). Several Air Force installations take advantage of purchasing energy derived from renewable sources or directly utilizing renewable energy. Renewable energy sources, along with all other energy sources, are captured and reported in DUERS.

Conclusion

After analyzing all previous literature summarized in this chapter, two conclusions can be made. First, weather parameters are paramount in deriving an energy model that accurately reflects energy consumption, with outdoor air temperatures as the single most important factor. Second, multiple regression analysis was routinely performed to assess the energy consumption explained by weather characteristics and was proven to be the most effective statistical method used. These two conclusions create the foundation for this thesis effort, providing insight into important influential factors for energy consumption at Air Force installations, while allowing flexibility to add other factors yet to be addressed by previous research. The end state will be the creation of a model that accurately predicts energy consumption at all Air Force installations. Finally, an understanding of the energy source requirements will assist in conducting trend analysis on energy consumption.

Chapter III. Methodology

This chapter provides an overview of the multiple linear regression analysis used to develop a predictive model of energy consumption at Air Force installations. The chapter will begin with a detailed account of the data collection process and the population selection criteria, followed by a six-step multiple linear regression process summarized by McClave, Benson, and Sincich (2005). During the discussion of these steps, detailed information regarding the development of the model and statistical tools utilized to analyze the data were provided in order to establish a plan to address the primary research question. Finally, the chapter will conclude with the statistical methods relied upon to conduct trend analysis to answer the final two research questions.

Data Collection

In order to adequately address the research questions identified in Chapter I, data pertaining to energy consumption and weather parameters were required. Thus, data were collected from two independent sources. First, energy consumption data, including base, major command (MAJCOM), million British Thermal Units (MBTU) of energy consumption per month, and square footage, were obtained from the Air Force Civil Engineer Support Agency (HQ AFCESA) located at Tyndall Air Force Base, Florida. AFCESA collected the energy consumption data from the Defense Utility Energy Reporting System (DUERS), as reported by each Air Force installation. The timeframe of the energy consumption data was from October 1985 to September 2006, encompassing 22 fiscal years of historical data. Second, weather parameters, including heating degree-days (HDD), cooling degree-days (CDD), wind speed (WS), and relative humidity (RH), were provided by the Air Force Combat Climatological Center (AFCCC), located in Asheville, North Carolina. Data were captured from the same time period as was the energy consumption data, from October 1985 through September 2006. The weather parameters above (HDD, CDD, wind speed and relative humidity) were selected primarily on their significance as evidenced in the empirical literature addressed in the previous chapter.

Population

The population in this thesis consisted of all active duty Air Force installations that initially submitted energy consumption data into DUERS beginning in 1985. Two criteria were placed on the population: 1) the installation must have submitted energy consumption data into DUERS for the timeframe of October 1985 to September 2006 and 2) weather data for the installation must have been available from AFCCC. The first criteria excluded all active duty installations that were previously closed as part of base realignment and closure actions. By applying these two criteria, 78 installations were excluded from the total population of 158 active duty bases. This left 80 active duty Air Force installations (National Guard and Reserve installations were excluded) widely dispersed throughout the contiguous United States, Alaska, Azores, Germany, Greenland, Guam, Hawaii, Italy, Japan, Korea, Spain, Turkey, and the United Kingdom. The dependent and independent variables that were analyzed are described below.

Multiple Linear Regression Model Development

The focus of this research effort was to determine the effects of weather on energy consumption, as stated in Chapter I. As identified in Chapter II, the most common technique employed by previous researchers in empirical literature was the use of multiple linear regression (Lam, 1998; Eto, 1988; Valor, Meneu & Caselles, 2001; Sailor & Munoz, 1997; Pardo, Meneu & Valor, 2002). According to Kutner, Nachtsheim, and Neter (2004), "regression analysis is a statistical methodology that utilizes the relation between two or more quantitative variables so that a response or outcome variable can be predicted from the other, or others" (p. 2). Kutner et al. (2004) also state "a regression model is a formal means of expressing the two essential ingredients of a statistical relation: (1) a tendency of the response variable Y to vary with the predictor variable X in a systematic fashion and (2) a scattering of points around the curve of statistical relationship" (p.5).

By using linear regression, a determination can be made whether selected quantitative weather variables exhibit any relationship or influence on the energy consumption dependent variable. A relationship between two variables can be expressed by a mathematical equation, as shown below (Kutner et al., 2004):

$$Y = f(X) \tag{4}$$

where Y equals the dependent variable and X equals the independent variable. This equation can then be transformed to create a multiple, first-order linear regression equation as shown below (Kutner et al., 2004):

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_{p-1} X_{i,p-1} + \varepsilon_i \quad (5)$$

where Y_i equals the dependent variable value in the ith trial, $X_{i1}, \ldots, X_{i,p-1}$ equals the independent variable values in the ith trial, $\beta_0, \beta_1, \ldots \beta_{p-1}$ equals the regression coefficients or parameters, ε_i equals the random error term, and i equals 1, …, n. The y-intercept, β_0, along with the regression coefficients and associated independent variables compose the deterministic portion of the regression equation. The random error term, ε_i, composes the non-deterministic portion of the equation.

Four basic assumptions regarding the random error term, ε, are required to enable the proper use of regression analysis. The four assumptions are identified below (McClave et al., 2005, p.712):

> (1) The mean of the probability distribution of ε is zero. That is, the average of the values of ε over an infinitely long series of experiments is zero for each setting of the independent variable x. This assumption implies that the mean value of y, $E(y)$, for a given value of x is $E(y) = \beta_0 + \beta_1 x$.
>
> (2) The variance of the probability distribution of ε is constant for all settings of the independent variable x. This assumption means that the variance of ε is equal to a constant, σ^2, for all values of x.
>
> (3) The probability distribution of ε is normal.
>
> (4) The values of ε associated with any two observed values of y are independent. That is, the value of ε associated with one value of y has no effect on the values of ε associated with other y values.

McClave et al. (2005) developed a six-step process used to assist in the creation of linear regression models. This methodology identifies the independent variables, estimates the variable regression coefficients, verifies the random error term assumptions, and evaluates the accuracy and usefulness of the model. These six steps are used in this thesis effort and are discussed in detail below.

Step 1: Hypothesize the Deterministic Components of the Model

In this first step, the independent variables to be used in the regression model are selected. Variables fall into two categories: quantitative or qualitative. Quantitative variables include data that are "recorded on a naturally occurring numerical scale" (McClave et al., 2005, p.17). Qualitative variables, in contrast, cannot be measured on a numerical scale; examples include gender or political affiliation. Thus, qualitative variables are grouped into categories. Once the qualitative variables are entered into regression equations, they are classified as dummy or indicator variables (Kutner et al., 2004). Coding of dummy variables can take any numerical form; however, in order to perform regression analysis on those dummy variables, special actions must be taken. Qualitative variables with c classes are represented by c-1 dummy variables in the model, where c is equal to the total number of qualitative categories. The cth class not represented in the model serves as the base case (Kutner et al., 2004).

In addition to quantitative and qualitative variables, interaction variables can also be created and included in linear regression models. Interaction variables are simply cross-product interaction effects of two or more quantitative variables. Interaction variables create reinforcement or interference effects on the dependent variable. Basically, the interaction variables affect both the y-intercept and the slope of the regression line. When an interaction occurs, the effect on the dependent variable from a change in the value of one of the cross-product variables depends on the other cross-product variable value(s) (McClave et al., 2005).

Independent quantitative variables used in this thesis effort were selected from those identified in literature as having predictive effects on energy consumption as identified above. Independent qualitative variables were chosen to facilitate the creation of a robust model that will accurately represent energy consumption figures for each Air Force installation. All independent variables will be tested for their predictive capacity; however, only the most predictive variables will remain in the final model.

Step 2: Estimate the Unknown Model Parameters

This second step uses the data gathered on the independent and dependent variables to estimate each unknown model parameter. Variable data are entered into a predictive analysis software program, which conducts numerous simultaneous linear regression calculations in an attempt to fit the values to a model. When fitting the values to a model in this manner, a method must be used to evaluate the fit of the model; the method of least squares is one such method. This least squares method attempts to minimize the sum of squares of the errors (SSE) in the regression line, thus enabling the best values of the regression coefficients to be determined. These regression coefficients are calculated in such a manner as to minimize the difference between the actual and predicted dependent variable values.

Step 3: Specify the Probability Distribution of the Random Error Term

In this step, the random error term's probability distribution is specified and the standard deviation of this distribution is estimated. As stated in the error term assumptions above, the random error is assumed to be independent, have a normal probability distribution with a mean of zero, and variance equal to σ^2. Since the σ^2 represents the variance of the random error, it is an extremely important measure in the development of the model as it predicts the actual values of the dependent variable. Thus, a large value of σ^2 implies that large random error values exist, indicating a large deviation between the predicted and actual dependent values. The variance, however, is rarely known and must be estimated. Again, the predictive analysis software program is used to calculate this measure by dividing the SSE by the difference between the number of observations and the number of estimated regression coefficients (McClave et al., 2005).

Step 4: Verify the Assumptions on the Random Error Term

Once regression analysis is applied to the independent and dependent data sets and a multiple linear regression model is produced, analysis must then be accomplished to verify the random error term assumptions are still valid. This is accomplished through a series of validation tests, primarily involving residual analyses. As each random error assumption is validated, the reliability of the model is improved. It is important to note that when using linear regression in practical applications, it is rare that all random error term assumptions are met; however, as long as the departure from the assumptions is not too large, the model will still provide useful results (McClave et al., 2005).

The analysis begins with the estimation of the random error, which is found by determining the difference between the actual dependent value and the estimated mean. This estimated error is known as a residual and is integral in the assumption validation tests. Residuals can then be plotted through a series of graphical methods to test the random error assumptions.

Testing the first assumption, which states the mean of the probability distribution of the error term is zero, can be accomplished by producing a scatter plot of residuals and predicted values. If the data are randomly distributed around the zero residual line without a discernable pattern, the scatter plot indicates a mean of zero. This plot will be produced to verify the first assumption.

The second assumption to be checked is whether the variance of the probability distribution is constant. Residual plots are also used to verify this assumption. The residuals and standardized predicted values are plotted and evaluated in the same manner as the first assumption. Standardized predicted values are those values that are transformed by dividing the difference between the mean predicted value and the predicted value by the standard deviation of the predicted value. This produces standardized predicted values with a mean of zero and a standard deviation of one (SPSS tutorial, 2007). Once the scatter plot is produced, a random distribution clustered around the residual zero line is desired, indicating a constant variance.

The third assumption regarding a normal probability distribution is verified through two graphical tools consisting of a histogram and a probability plot of the residuals. The histogram is developed by fitting the residuals to a normal distribution curve. If the residuals closely follow the normal curve, the distribution is considered normal. The second plot involves comparing the residuals to a normal probability plot depicted by a straight line. Once the residuals are plotted along the straight line, a visual assessment is conducted. If the residuals closely follow the straight line, the distribution is considered normal. Both of these descriptive displays will be utilized.

The final assumption involves the random error terms being independent of each other. This assumption is verified through the use of the Durbin-Watson test statistic, which detects autocorrelation in residuals. Autocorrelation is defined as "the correlation between time series residuals at different points in time" (McClave et al., 2005, p.1046). The SPSS 15.0 for Windows predictive software package calculates this test statistic, in which values range between zero and four. Values close to two indicate no autocorrelation, while values above and below two indicate positive and negative autocorrelation, respectively. Time series data, such as the data used in this thesis effort, is commonly subjected to positive autocorrelation. Violation of this independence assumption affects the precision of the regression model, but not the accuracy of the estimates of the coefficients (McClave et al., 2005). The Durbin-Watson test statistic will be calculated and analyzed in this thesis effort.

In addition to validating the random error term assumptions, statistical outliers and influential data points will be investigated using residual analyses. According to

McClave et al. (2005), outliers are data points that “are unusually large or small relative to the other values in a data set” (p. 100). Residual analyses are beneficial in detecting deviations in the regression model. Approximately 95 percent of the residuals should fall within two standard deviations and 99 percent within three standard deviations. Residuals that fall outside of three standard deviations are thus considered outliers and require further investigation to determine the cause. A decision must be made to either keep the outlier in the data set or reject it. Outliers will be identified statistically by reviewing standardized residual data. Similarly, influential data points affect regression models by skewing the data and producing misleading results. Influential data points will be detected through the use of the Cook’s distance measure. The Cook’s distance measure “considers the influence of the *i*th case on all *n* fitted values” (Kutner et al., 2004, p.402). While no set rules govern the results of this measure, large values indicate the possibility of influence and will be investigated. The SPSS 15.0 for Windows software package calculates the Cook’s distance measure and will be analyzed to detect any influential data points.

Step 5: Statistically Evaluate the Usefulness of the Model

This step is conducted to evaluate the statistical significance of the multiple linear regression model produced from the previous four steps. Analysis of the model begins with inferences regarding the estimated regression coefficients. The regression coefficients are subjected to hypothesis testing to ensure they are statistically significant. Two hypothesis tests are used for each coefficient: (1) the null hypothesis says the coefficient is equal to zero and (2) the alternate hypothesis says the coefficient is not equal to zero. A *p*-value is calculated for each regression coefficient and compared to an alpha of 0.05. If the *p*-value is greater than 0.05, the null hypothesis cannot be rejected. Similarly, if the *p*-value is less than 0.05, the null hypothesis can be rejected, meaning the regression coefficients are statistically different than zero. The SPSS 15.0 for Windows software package provides a detailed table with corresponding regression coefficients and *p*-values, allowing rapid identification of statistically significant independent variables.

The next test conducted involved an analysis to determine the existence of multicollinearity. Multicollinearity in regression exists when two or more independent variables are highly correlated, making it difficult to determine if redundant effects are imposed on the dependent variable (Kutner et al., 2004). SPSS 15.0 for Windows calculates variance inflation factors (VIF), which provide insight into multicollinearity for each variable. When VIF values are greater than ten, this indicates that multicollinearity may be present and the identified variables are causing excessive influence in the least squares method (Kutner et al., 2004). The VIF values will be analyzed for each dependent variable.

The remaining statistical test involves the multiple coefficient of determination value, R^2, which provides an indication of how well the model fits the data set. The R^2 "represents the fraction of the sample variation of the *y* values that is explained by the least squares prediction equation" (McClave et al., 2005, p.788). This value, which ranges between zero and one, is the explained variability divided by the total variability. Thus, the higher the R^2 value, the more the variation in the dependent variable is explained by the independent variables. Unfortunately, the R^2 value can be increased simply by adding additional independent variables. However, another measure, called the adjusted multiple coefficient of determination, compensates for this negative aspect by accounting for sample size and the number of parameters included in the model. Therefore, the adjusted R^2 value provides a more accurate measure of model fit, and will be analyzed in this research effort.

Step 6: Use the Model for Prediction or Estimation

The final step tests the model's predictive ability by applying the regression model to a subset of the data and comparing the predicted values to the actual values. A portion of the data is commonly set aside and not used in the creation of the regression model. This portion is then analyzed by the regression model to determine its predictive capabilities. For this thesis effort, one fiscal year (2006) of data was not used in constructing the regression model, but was used to compare the model's predicted values with the actual values.

Trend Analysis

Trend analysis is beneficial in determining whether events are recurring in a discernable pattern and enable forecasting or prediction of future similar events. Trend analysis also provides a mechanism in which a researcher can make informed decisions or recommendations based on the trend data. Trend analysis will be used to attempt to address the second and third research objective identified in Chapter I.

The research question regarding which months are best/worst in terms of energy consumption will be addressed by analyzing additional graphical methods. Monthly energy consumption per square foot data will be plotted through the period of October 1985 to September 2006 to determine whether trending can be predicted. Throughout the year, each individual Air Force installation experiences varying degrees of heating and cooling requirements. Commonly, a transitional period will exist where neither heating nor cooling is required, in which the actual outdoor air temperature is close to the reference, or base, temperature of 65 degrees Fahrenheit (18.3 degrees Celsius). This would drive both HDD and CDD to remain relatively close to zero, resulting in minimal energy consumption per square foot values. The graphs produced will provide insight into the energy consumption levels per month.

Similarly, the research question regarding which energy sources (electricity, natural gas, or other) vary the greatest between the heating and cooling seasons will also be analyzed by graphical methods. Recalling the pie chart of facility energy source usage shown in Figure 2-2, electricity and natural gas far exceeded the remaining energy sources in terms of overall usage. Thus, those two sources were selected for comparison. The category "other" includes fuel oil, coal, purchased steam, liquid petroleum, and propane. Series of plots depicting levels of energy sources per month will be produced to determine which energy source varies the most. The differential between the most energy intensive winter and summer months will be determined, thus providing evidence into which energy source varies the greatest throughout the year.

Summary

This chapter provided the methodology used to create and analyze a multiple linear regression equation and conduct trend analysis on pertinent data. First, the data collection and population selection process was described. Then, a synopsis of the six-step regression model process was presented, followed by a detailed account of the requirements involved in each step. Finally, the trend analysis component of this effort was addressed. This chapter established the roadmap for the next chapter in which the actual energy consumption and weather variables, along with the qualitative variables, will be presented and analyzed.

Chapter IV. Results

This chapter presents a summary of the results of the analysis with regard to the research questions identified in Chapter I. Statistical methods, through the use of graphical tools, were employed to assess possible relationships between the selected weather parameters and energy consumption. Multiple linear regression analysis was used to determine the impact that weather conditions have on energy consumption. Multiple linear regression analysis was also used to evaluate what effects major commands, climate zones, and mission categories contributed to the model. Finally, graphical methods were used to evaluate overall energy consumption trends to determine which months were most/least affected by the weather variables and which energy sources varied the most between the winter and summer months.

Variables

Two types of variables were included in this regression model: quantitative (energy and weather related) and qualitative (demographic). The quantitative variables included those obtained from the Air Force Civil Engineer Support Agency (AFCESA) and the Air Force Combat Climatological Center (AFCCC) as discussed in Chapter III. Qualitative variables included demographic-related variables that cannot be measured on a quantitative scale. The qualitative variables were selected in order to account for additional variation in energy consumption and to provide a more robust, overarching model. Both types of variables are discussed in depth below.

Variables Related to Energy Usage and Weather

As identified in Chapter II, several weather variables have proven predictive in regards to energy consumption. Outdoor air temperature, wind speed, and relative humidity indicated some relation with energy consumption in each of the economic sectors. Each of the dependent and independent quantitative variables selected for this research effort is discussed below.

Thousand British Thermal Units per Square Foot (KBTU/SF)

This variable is a measure of the total energy consumed per facility square foot and serves as the dependent variable in this research effort. This measure is reported monthly in DUERS by each installation as million British Thermal Units (MBTU), but was changed to KBTU simply for readability. Several energy sources including electricity, fuel oil, natural gas, and coal contribute to this variable. However, for the purposes of this thesis, the total energy consumption quantity reported, regardless of energy source, was utilized in the energy model. Monthly reported KBTU quantities were summed to provide a fiscal year output for each installation. After the summation of the energy consumption, it was divided by the total facility gross square footage as reported in the real property records of each respective installation to create the KBTU/SF measure. This step was conducted to standardize the energy consumption quantity by square footage to allow for appropriate comparisons between all 80 installations.

Heading Degree-days (HDD)

This independent variable represents the sum of daily heating degree-days experienced at each installation. AFCCC records daily heating degree-day data and provides a monthly total. The minimum value for HDD is zero. For example, in warmer climates, such as experienced in Hawaii and Guam, the sum of HDDs could be zero for the month, or quite possibly, the entire year. This independent variable was selected due to its influence on energy consumption, as detailed in Chapter II.

Cooling Degree-days (CDD)

Similar to HDD, this independent variable represents the sum of daily cooling degree-days experienced at each installation. AFCCC records daily cooling degree-day data and provides a monthly total. The minimum value for CDD is zero. For example, in cooler climates, such as experienced in Greenland, the sum of CDDs could be zero for the month or for the year. This independent variable was selected due to its influence on energy consumption, as detailed in Chapter II.

Wind Speed (WS)

This independent variable represents the average monthly wind speed experienced at each installation. AFCCC records daily average wind speeds and provides a monthly average; these values were then used to calculate the annual average wind speed. This independent variable was selected due to its influence on energy consumption, as detailed in Chapter II.

Relative Humidity (RH)

This independent variable represents the average monthly relative humidity experienced at each installation. AFCCC records the daily average relative humidity and provides a monthly average. Similar to wind speed, the annual average relative humidity was calculated by averaging the monthly relative humidity averages. This independent variable was selected due to its influence on energy consumption, as detailed in Chapter II.

Interaction Variables

Six independent variables represent the interaction effects between HDD, CDD, WS, and RH. The six variables are HDD * WS, HDD * RH, CDD * WS, CDD * RH, HDD * CDD, and WS * RH. These six additional independent variables were selected to measure their interaction effects on the dependent variable, KBTU/SF.

Variables Related to Demographics

The following qualitative independent variables were chosen with the intent of creating one overarching multiple linear regression model that would be capable of predicting energy consumption at each Air Force installation. Each of the following three sets of independent variables was coded as dummy variables and statistically evaluated. Each dummy variable has only two allowable value: zero or one. If these candidate variables prove to have low predictive value in the model, they will be discarded.

Major Commands (MAJCOM)

These independent variables represent seven of the nine major commands in the Air Force. The MAJCOMs include Air Combat Command (ACC), Air Education and Training Command (AETC), Air Force Materiel Command (AFMC), Air Mobility Command (AMC), Pacific Air Forces Command (PACAF), Air Force Space Command (AFSPC), and the United States Air Forces in Europe (USAFE). The other two major commands consist of the Air Force Reserve Command (AFRC) and the Air Force Special Operations Command (AFSOC). The installations within these two MAJCOMs were not included in this analysis for two reasons: (1) daily operations at Reserve installations are not equivalent to those at active duty installations and (2) adequate weather data was not readily available for a majority of Reserve installation. Additionally, the two installations within the Air Force Special Operations Command (AFSOC), Moody Air Force Base and Hurlburt Air Force Base, were recoded and included in the ACC category. This step was taken due to the limited number of bases in AFSOC and the similar missions of AFSOC and ACC. Additionally, Moody historically was an ACC installation and only recently changed major commands. Finally, Bolling Air Force Base and the United States Air Force Academy were recoded and included in the AETC category. Again, this step was taken due to their similar missions with AETC. For this analysis, ACC served as the base case and was not be included in the actual regression model. These variables were selected to determine if the installations' respective MAJCOMs influenced the overall energy model.

Climate Zone (CZ)

These five independent variables represent the five different climate zones in which the installations can be categorized. For this analysis, Climate Zone 1 will serve as the base case and will not be included in the actual regression model. Placement into the various climate zones was dictated by the HDD and CDD totals experienced by the respective installation. The metrics used to calculate the applicable CZ are shown below (Energy Information Administration, 2007):

Climate Zone 1: less than 2,000 CDD and greater than 7,000 HDD annually
Climate Zone 2: less than 2,000 CDD and 5,500 - 7,000 HDD annually
Climate Zone 3: less than 2,000 CDD and 4,000 – 5,499 HDD annually
Climate Zone 4: less than 2,000 CDD and less than 4,000 HDD annually
Climate Zone 5: 2,000 CDD or more and less than 4,000 HDD annually

Mission Type

These four independent variables represent four possible mission types in which the installations can be categorized. The four mission types are Combat Flying; Non-Combat Flying; Support; and Strategic/Intelligence, Surveillance, and Reconnaissance (Strategic/ISR). For this analysis, Combat Flying will serve as the base case and will not be included in the actual regression model. These four mission types were purposely designed in a broad manner to capture the various major missions at each installation without creating an excessive number of categories. Bases classified under the Combat Flying mission type are those installations in which a majority of the installation's overall mission is to conduct flying operations in which aircraft are subjected to combat missions. Non-Combat Flying installations represent those bases in which flying operations occur frequently but are not subjected to combat operations. Installations included in this mission category commonly conduct pilot training operations. Next, the Support mission represents those bases that do not have a flying mission or have a very small flying component. Bases included in this category commonly conduct personnel training or research activities constituting a significant majority of its mission. Finally, bases in the Strategic/ISR category focus primarily on space launch, satellite operation and tracking, missile launch warning, space surveillance, or intercontinental ballistic missile operations. Each of the installations and their respective categories are provided in Appendix A.

Variable Analysis

As outlined in Chapter III, the six-step approach described by McClave et al. (2005) was used to create the multiple regression model. For the first step, once the dependent and independent variables were initially selected, statistical analysis was conducted to observe the relationships between the variables. This step was crucial to ensuring the variables behaved in a manner that was conducive to multiple linear regression. The statistical analysis was accomplished through the use of descriptive statistics. McClave et al. (2005) explain that "descriptive statistics utilizes numerical and graphical methods to look for patterns in a data set, to summarize the information revealed in a data set, and to present the information in a convenient form" (p. 5). Common graphical representations of data include scatter plots, box-and-whisker plots, and histograms. Thus, to ensure a relationship existed between the variables, similar methods were employed in this research effort, which provided visual proof of those relationships and highlighted erroneous data points.

Scatter Plots

The use of scatter plots was beneficial in visually determining the relationship between two variables. Scatter plots were created to check the relationship between the dependent variable, KBTU/SF, and the various independent variables (HDD, CDD, WS, and RH). An additional variable was added, which was the sum of the HDDs and CDDs, to further investigate the relationship between degree-days and energy consumption. Figures 4-1, 4-2, 4-3, 4-4, and 4-5 display the relationships between the dependent variable and the respective independent variables. Figure 4-1 clearly indicates that as the number of HDDs increases, the KBTU/SF increases. In Figure 4-2, with CDD as the independent variable, it appears that as CDD increases, the KBTU/SF slightly decreases. In Figure 4-3, the sum of the HDDs and CDDs was plotted against KBTU/SF to determine which of the two variables had the greatest influence over the dependent variable. The plot indicates that HDD provides more influence on KBTU/SF than does CDD and mirrored the relationship shown in Figure 4-1. Figure 4-4 denotes a very slight increase in KBTU/SF with an increase in wind speed. Finally, Figure 4-5 shows a very slight decrease in KBTU/SF with an increase in relative humidity. These five scatter plots provided insight into the potential influence each independent variable had on the dependent variable; they also displayed possible outlier data points.

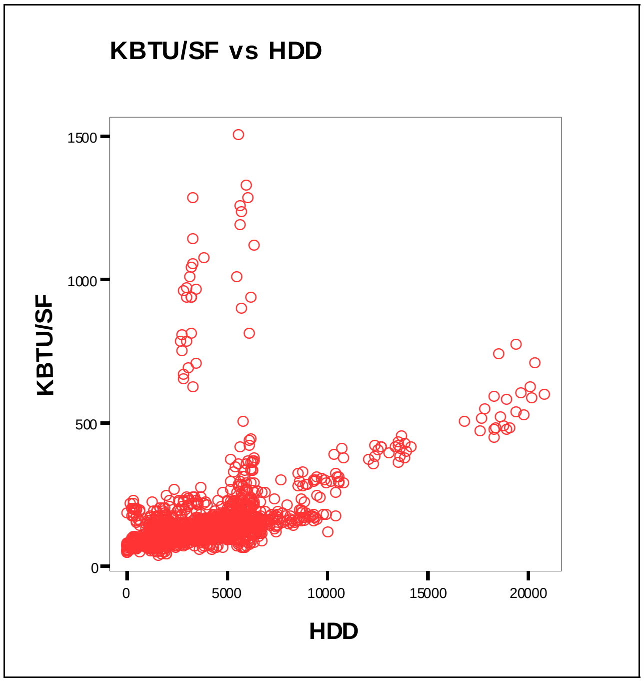

Figure 4-1. Scatter plot of KBTU/SF vs. HDD

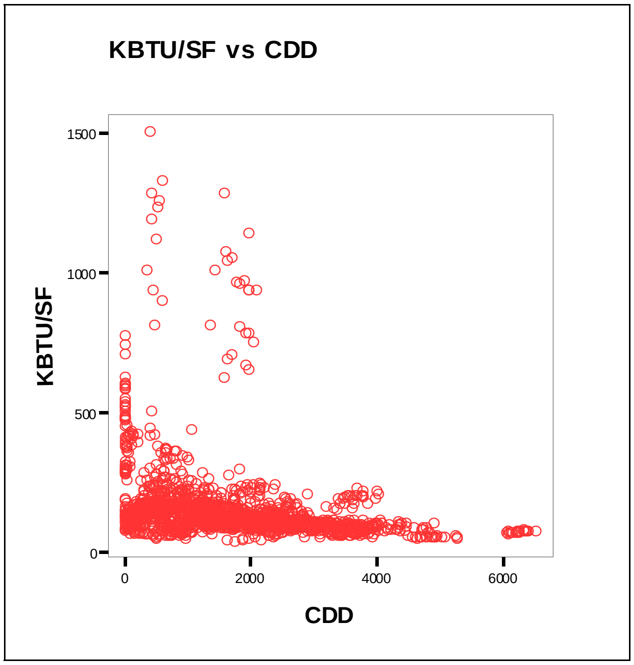

Figure 4-2. Scatter plot of KBTU/SF vs. CDD

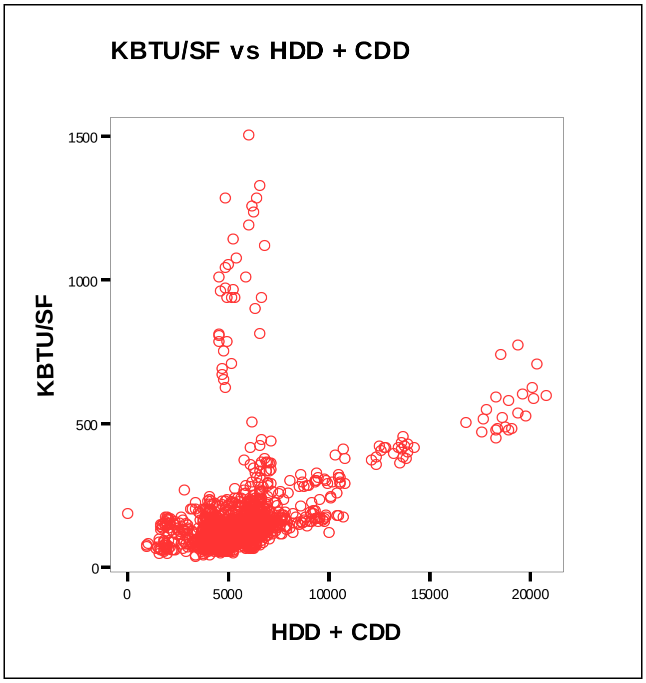

Figure 4-3. Scatter plot of KBTU/SF vs. HDD + CDD

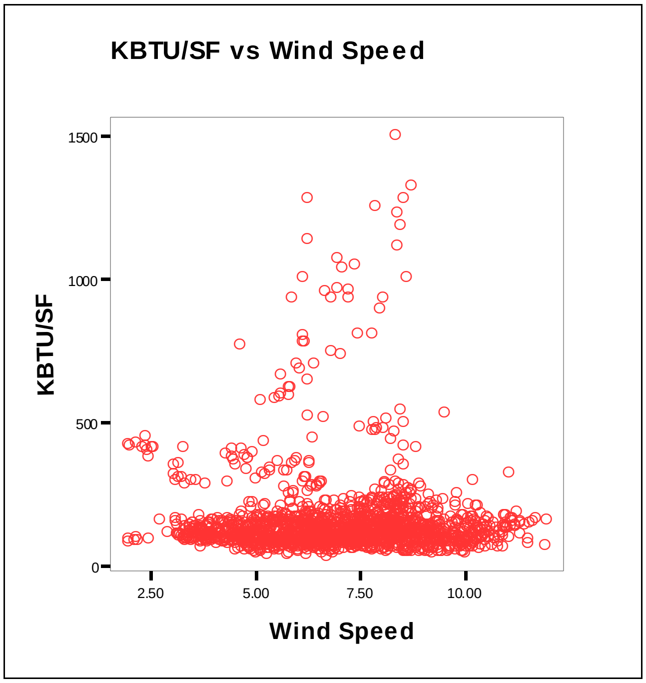

Figure 4-4. Scatter plot of KBTU/SF vs. WS

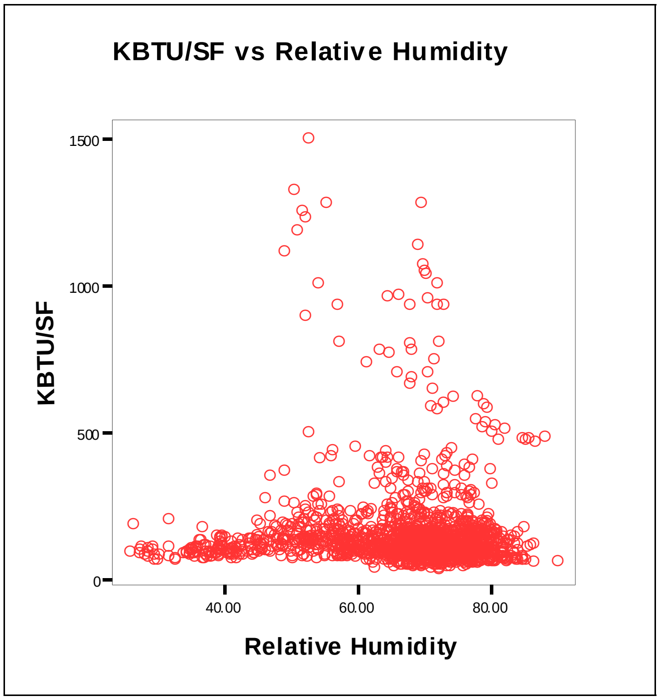

Figure 4-5. Scatter plot of KBTU/SF vs. RH

Box-and-whisker Plot

Box-and-whisker plots, according to McClave et al. (2005), are useful in detecting outliers. The box-and-whisker plot was also beneficial in revealing seasonal trends in the data. Box-and-whisker plots display data in quartile fashion, in which the middle, or 50 percent, range falls within the box and the remainder inside the whiskers (McClave et al., 2005). Values that fall beyond the whiskers are potential outliers. For normally distributed data, less than one percent of the values are expected to fall beyond the whiskers. Figure 4-6 is a box-and-whisker plot that identifies the monthly KBTU/SF values over a five-year period, from January 2001 to December 2005. As noted in the figure, several outliers exist in the data and a seasonal trend is witnessed throughout the five-year period, with KBTU/SF peaks occurring in the winter months and low points seen in the summer months. Since the data shows a seasonality trend when using monthly data, a supporting argument is provided to use annual versus monthly data to account for the trend and to produce a better model. Using an annual approach might reduce the seasonal fluctuations observed throughout the year.

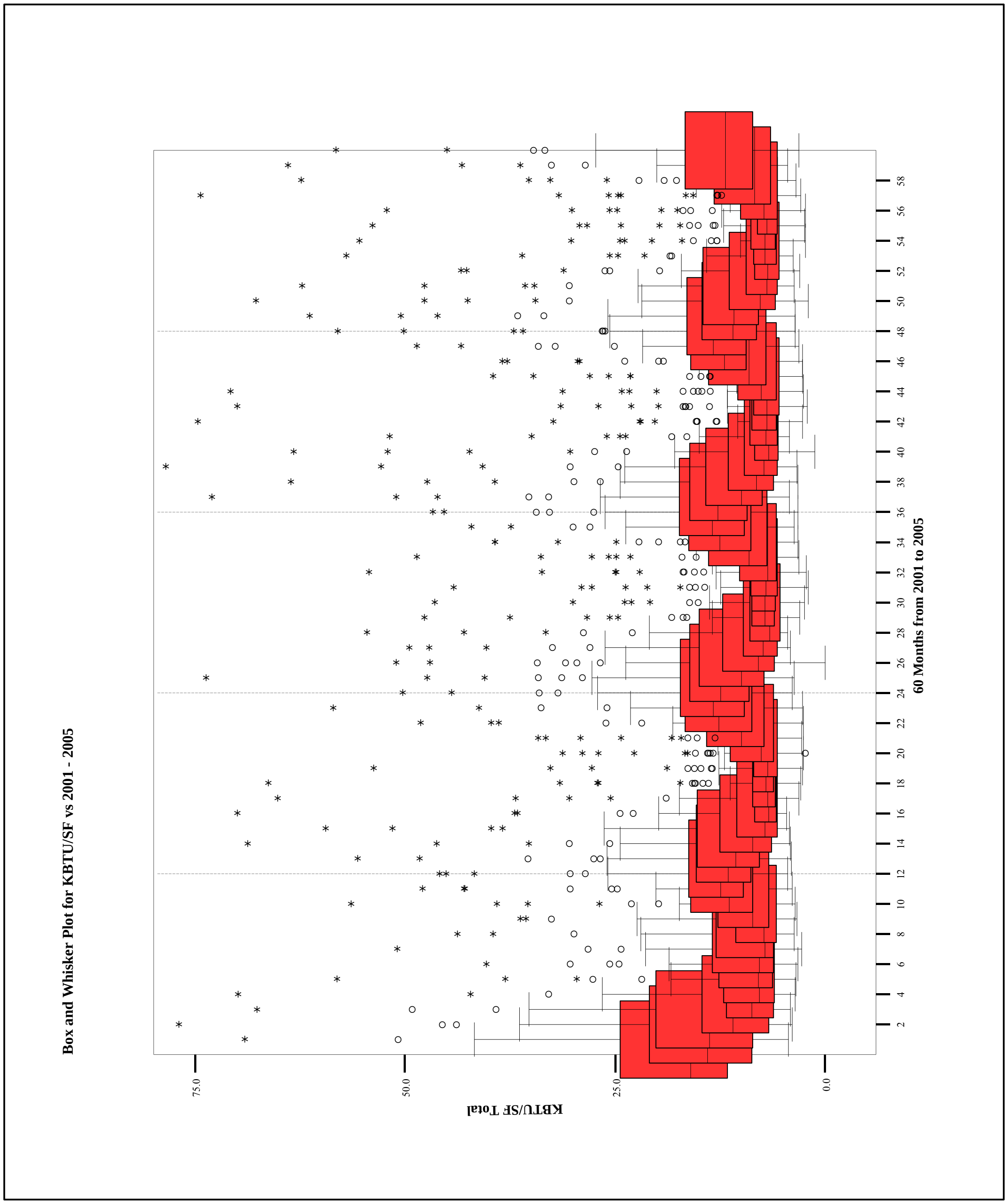

Figure 4-6. Box-and-whisker Plot of Scatter plot of KBTU/SF

Histograms

Histograms are commonly used to display the frequencies of data that fall in established class intervals (McClave et al., 2005). A histogram of the dependent variable was created to investigate the distribution of the data and visually inspect for outliers. Figure 4-7 shows the data is skewed right, indicating the existence of outliers. This further confirms the existence of possible erroneous data points, as seen in the scatter plots and box-and-whisker plots.

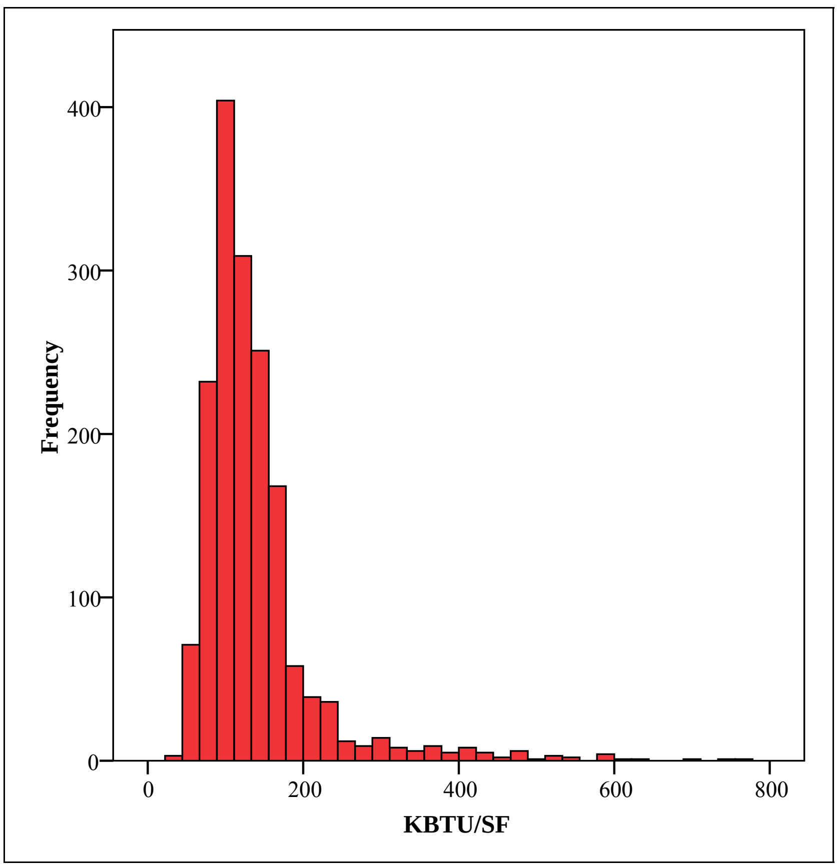

Figure 4-7. Histogram of KBTU/SF

Data Analysis

Initially, the data set was composed of monthly observations over the 22 fiscal year period involving 80 Air Force bases. This provided 21,120 observations for each variable. After reviewing Figure 4-6 and identifying the seasonality effect, the monthly data were aggregated to create annual data; this step minimized the seasonality effects. The creation of annual data reduced the observations from 21,120 to 1,740 for each variable. Tests were then conducted to identify outliers within the data.

As shown in the earlier scatter plots and box-and-whisker plots, numerous outliers were present. Outliers primarily consisted of installations that had extreme values of energy consumption per square foot over the entire time period observed. These outliers were analyzed for possible removal from the data. Four separate tests were conducted to detect outliers. First, a box-and-whisker plot of KBTU/SF was created using the annual data to display installations that experienced significantly high energy consumption rates per square footage. Figure 4-8 shows this box-and-whisker plot. As discussed in the box-and-whisker plot section above, data points that fall outside of the whiskers are considered outliers. The circle (o) denotes outliers while the asterisk (*) denotes extreme outliers. SPSS 15.0 for Windows calculated these outliers and extreme outliers by applying the following criteria: if the value of the data was smaller (or larger) than 1.5 box-lengths from the lower fourth (upper fourth), it was classified as an outlier and if the value of the data was smaller (or larger) than 3.0 box-lengths from the lower fourth (upper fourth), it was classified as an extreme outlier. The box-length was defined as the interquartile range. The upper fourth represents the top of the box while the lower fourth represents the bottom of the box. The area between the upper and lower fourths is the interquartile range. Installations experiencing outlier or extreme outlier data points were Arnold, Cheyenne Mountain, Eielson, Elmendorf, Hanscom, Moron, New Boston, and Thule. These installations were not immediately deleted from the analysis based on this test alone.

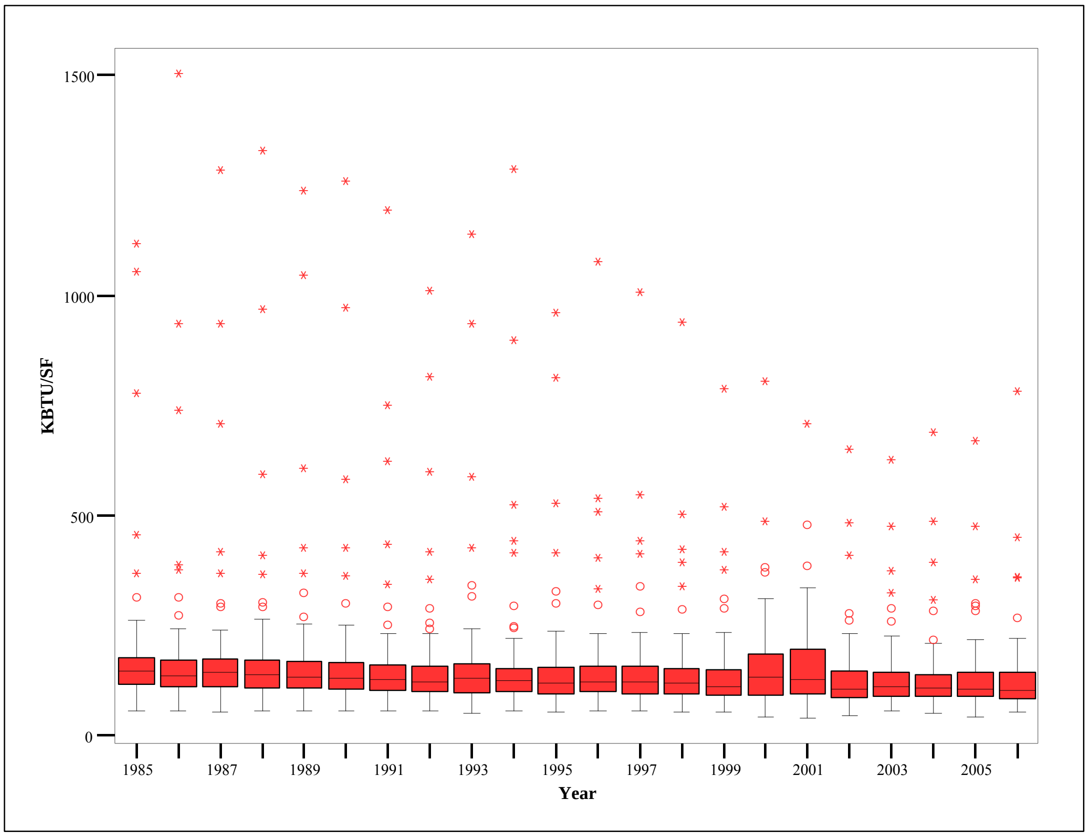

Figure 4-8. Box-and-whisker Plot of Annual KBTU/SF

The next three tests involved the use of descriptive statistics, primarily the mean and standard deviation. For these tests, the KBTU/SF value was evaluated using HDD, CDD, and summed HDD and CDD values. These tests created three additional measures to determine installation energy intensity levels. The means and standard deviations of each of the three tests were calculated and used to evaluate for potential outliers. Using a +/- 2.5 standard deviation factor, several installations were again identified as having outlier data points. The selected standard deviation factor (+/- 2.5) ensured that approximately 99 percent of the data fell within the data range. Thus, if the data point exceeded the +/- 2.5 factor, it represented one percent of the data range and was classified as an outlier. Installations with values that exceeded the +/- 2.5 standard deviation factor were Arnold, Cape Canaveral, Cheyenne Mountain, Hanscom, Lajes, and New Boston.

The box-and-whisker plot provided an initial observation of the installation's energy consumption without regard to any weather parameters. By including HDD, CDD, and summed HDD and CDD values, it provided a more robust evaluation tool to detect outliers. Installations, such as Eielson, Elmendorf, and Thule, which experience cold climates and high HDD values, would have been eliminated from the sample size based solely on their energy consumption per square foot values. This would have unnecessarily reduced the sample size without further refinement of the data. The next three series of tests exposed two additional installations that experienced significantly high levels of energy consumption per square footage when weather parameters were applied. Based on these four tests, the following installations were excluded from the sample: Arnold, Cape Canaveral, Cheyenne Mountain, Hanscom, Lajes, and New Boston. By excluding these six installations, the observations were reduced to 1,626 data points for each variable, covering 74 Air Force installations. In order to effectively test the predictive capabilities of the model, data pertaining to fiscal year 2006 will be reserved and not used in the creation of the regression model. Thus, the total number of data points was reduced to 1,552.

Regression Model

Based on the preliminary quantitative and qualitative variables identified for this research, the initial response function for the regression model was:

$$Y_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_1 X_3 + \beta_6 X_1 X_4 + \beta_7 X_2 X_3 + \beta_8 X_2 X_4 + \beta_9 X_1 X_2 + \beta_{10} X_3 X_4 + \beta_{11} X_5 + \beta_{12} X_6 + \beta_{13} X_7 + \beta_{14} X_8 + \beta_{15} X_9 + \beta_{16} X_{10} + \beta_{17} X_{11} + \beta_{18} X_{12} + \beta_{19} X_{13} + \beta_{20} X_{14} + \beta_{21} X_{15} + \beta_{22} X_{16} + \beta_{23} X_{17} \quad (6)$$

where Y_i = energy consumption (KBTU/SF) dependent variable
X_1 = Heating Degree-days (HDD)
X_2 = Cooling Degree-days (CDD)
X_3 = Wind Speed (WS)
X_4 = Relative Humidity (RH)
X_5 = {1 if AETC, 0 otherwise}
X_6 = {1 if AFMC, 0 otherwise}
X_7 = {1 if AMC, 0 otherwise}
X_8 = {1 if PACAF, 0 otherwise}
X_9 = {1 if AFSPC, 0 otherwise}
X_{10} = {1 if USAFE, 0 otherwise}
X_{11} = {1 if Climate Zone 2, 0 otherwise}
X_{12} = {1 if Climate Zone 3, 0 otherwise}
X_{13} = {1 if Climate Zone 4, 0 otherwise}
X_{14} = {1 if Climate Zone 5, 0 otherwise}
X_{15} = {1 if Non-Combat Flying, 0 otherwise}
X_{16} = {1 if Support, 0 otherwise}
X_{17} = {1 if Strategic/ISR, 0 otherwise}
$\beta_0, \beta_1, \ldots \beta_{p-1}$ = coefficients or parameters

This initial model was iteratively tested in an attempt to produce the most accurate energy consumption model for Air Force installations.

Based upon the empirical evidence provided in Chapter II and selected qualitative categorical measures, the variables listed in Table 4-1 were initially included in the overall model, excluding the base case qualitative variables (ACC, Climate Zone 1, and Combat Flying). Multiple linear regression analysis accomplished using SPSS 15.0 for Windows predictive analysis software. One specific form of linear regression, known as stepwise regression, was used to analyze the data. Stepwise regression systematically removes independent variables that are not statistically significant, leaving a model that represents only those independent variables that are statistically significant to the dependent variable.

Table 4-1. Regression Independent Variables

Independent Variables	**Categories or Measure By**
Heating Degree-days (HDD)	Number of HDDs per month/year
Cooling Degree-days (CDD)	Number of CDDs per month/year
Wind Speed (WS)	Average WS per month/year
Relative Humidity (RH)	Average RH per month/year
Interaction variable of HDD * WS	Product of HDD and WS
Interaction variable of HDD * RH	Product of HDD and RH
Interaction variable of CDD * WS	Product of CDD and WS
Interaction variable of CDD * RH	Product of CDD and RH
Interaction variable of HDD * CDD	Product of HDD and CDD
Interaction variable of WS * RH	Product of WS and RH
Major Command (MAJCOM)	ACC, AETC, AFMC, AFSPC, AMC, PACAF, USAFE
Climate Zone (CZ)	CZ 1, CZ 2, CZ 3, CZ 4, CZ 5
Base Mission	Combat Flying, Non-Combat Flying, Support, Strategic/ISR

The stepwise regression results of this analysis produced the following model in equation form:

$$\begin{aligned} Y_i = 37.903 + 0.032X_1 + 0.007X_2 - 0.001X_1X_3 + 39.897X_6 - 19.288X_{10} \\ -38.671X_{11} - 19.014X_{12} - 5.250X_{15} + 35.074X_{17} \end{aligned} \tag{7}$$

where Y_i = energy consumption (KBTU/SF) dependent variable
X_1 = Heating Degree-days (HDD)
X_2 = Cooling Degree-days (CDD)
X_3 = Wind Speed (WS)
X_6 = {1 if AFMC, 0 otherwise}
X_{10} = {1 if USAFE, 0 otherwise}
X_{11} = {1 if Climate Zone 2, 0 otherwise}
X_{12} = {1 if Climate Zone 3, 0 otherwise}
X_{15} = {1 if Non-Combat Flying, 0 otherwise}
X_{17} = {1 if Strategic/ISR, 0 otherwise}

Table 4-2 displays the results of the model, including the associated coefficients, *p*-values, and variance inflation factors (VIF) for each variable. As listed in the table, each *p*-value was less than 0.05, indicating that the associated variable was statistically significant to the regression model. Since stepwise regression was used, SPSS 15.0 for Windows automatically discarded variables with *p*-values greater than 0.05. The coefficient and VIF values will be discussed in more detail in the following sections.

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Table 4-2. Model Summary

Variable	Coefficient	*p*-value	VIF
Constant	37.903	0.000	
HDD	0.032	0.000	5.117
CDD	0.007	0.000	2.561
HDD * WS	-0.001	0.000	5.052
AFMC	39.897	0.000	1.048
USAFE	19.288	0.000	1.171
CZ2	-38.671	0.000	1.546
CZ3	-19.014	0.000	1.329
Non-Combat Flying	-5.250	0.014	1.077
Strategic/ISR	35.074	0.000	1.350

Model Diagnostic Testing

After creating the regression model, diagnostic testing was performed to assess the model for applicability and aptness, as detailed in Chapter II. As addressed in the previous chapter, assumptions regarding the random error term must be verified. First, Figure 4-9 verifies the assumption that the mean of the probability distribution of the error term is zero. This graph displays a scatter plot of residuals and predicted values. Since the data appear randomly distributed around the zero residual line without a discernable pattern, the scatter plot indicates a mean of zero. This plot validates the first assumption.

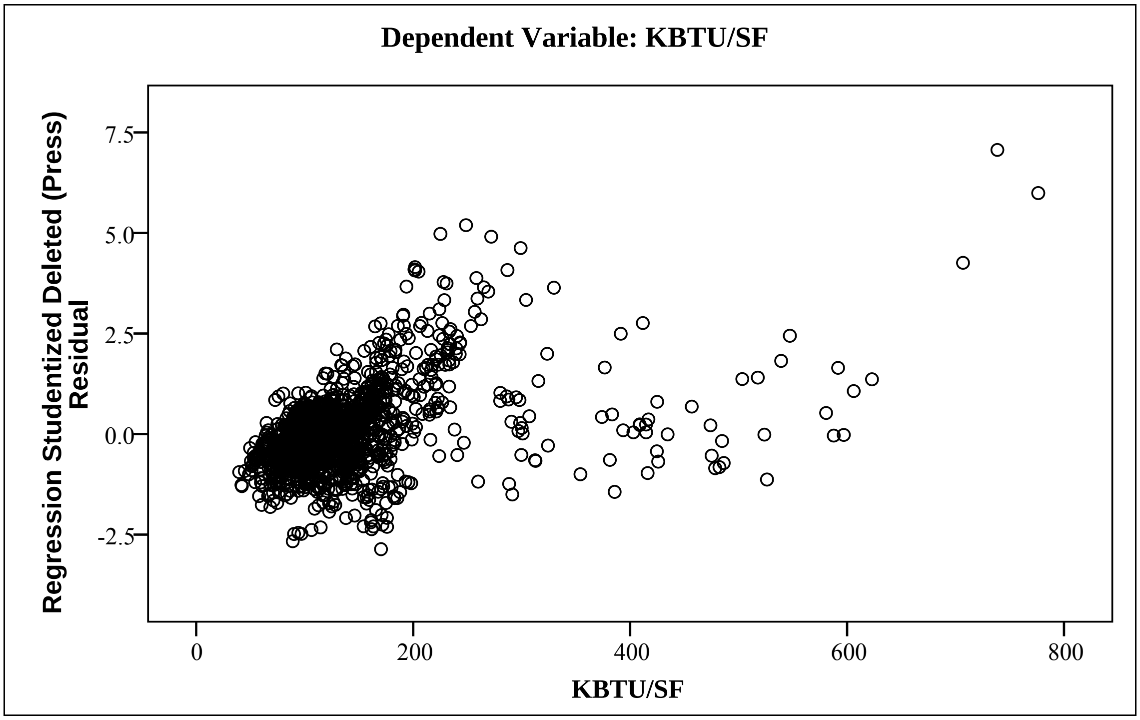


Figure 4-9. Scatter Plot of Residuals and Predicted Values of Energy Consumption

The second assumption checked was whether the variance of the probability distribution is constant. Figure 4-10 is a scatter plot of residuals versus standardized predicted values in which the data points are relatively evenly and somewhat randomly positioned above and below zero. This visually indicates that there are no problems with constant variance of the error terms. Again, the random distribution clustered around the residual zero line indicates validation of a constant variance. Thus, the second assumption is verified.

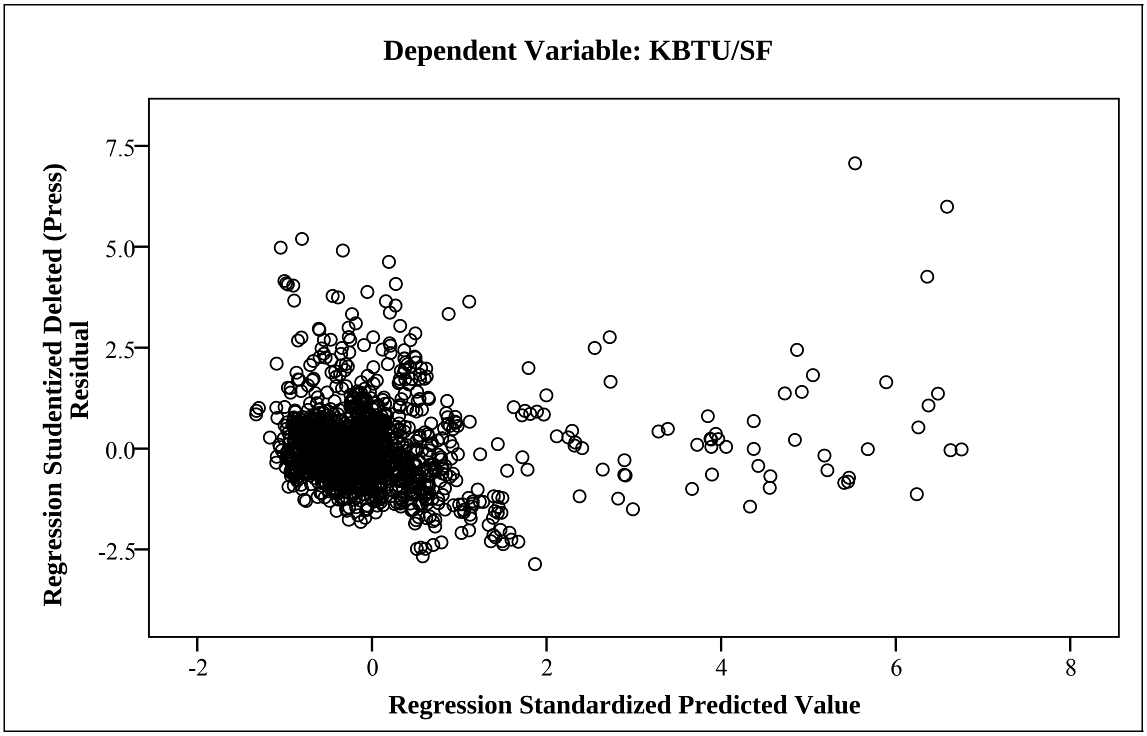


Figure 4-10. Scatter Plot of Studentized Residuals versus Standardized Predicted Value

Next, Figures 4-11 and 4-12 verified the assumption that the distribution of the error term is normal. Figure 4-11 displays a histogram of the standardized residual and the shape of the histogram closely follows the normal curve, thus satisfying the assumption. Figure 4-12 displays the normal probability plot of the regression standardized residual. The data closely follows the line, thus reconfirming the normality of the error terms.

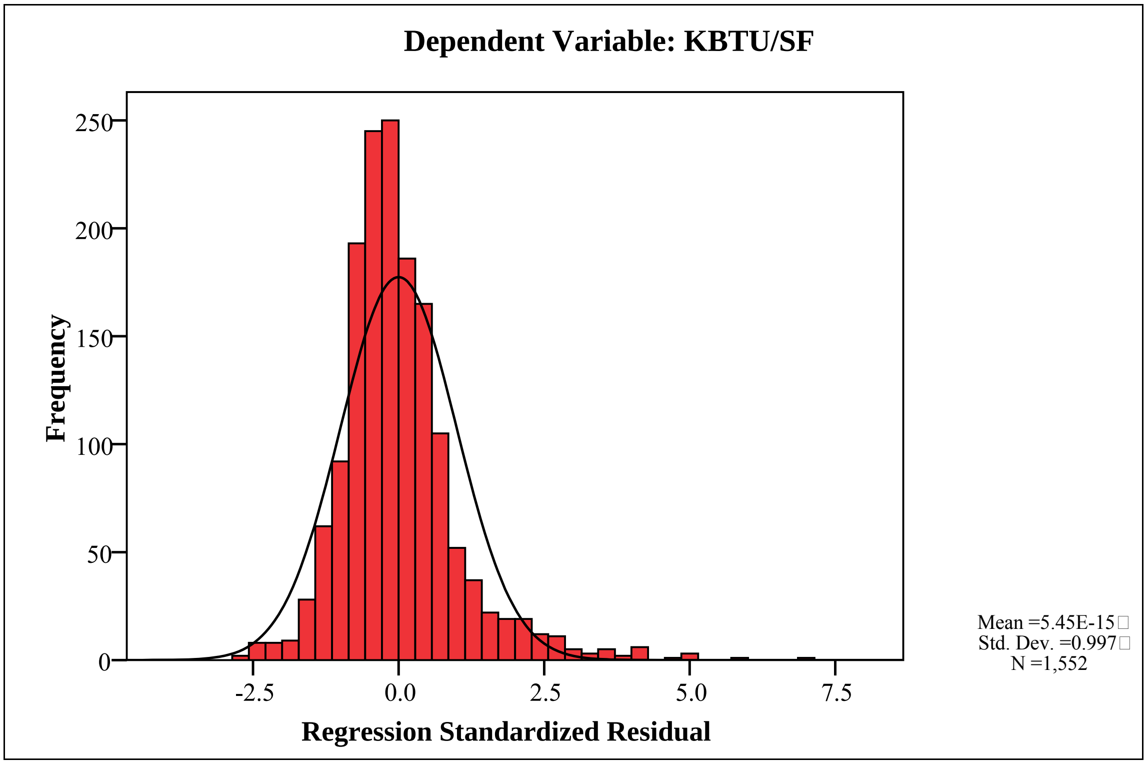


Figure 4-11. Histogram of Standardized Residuals

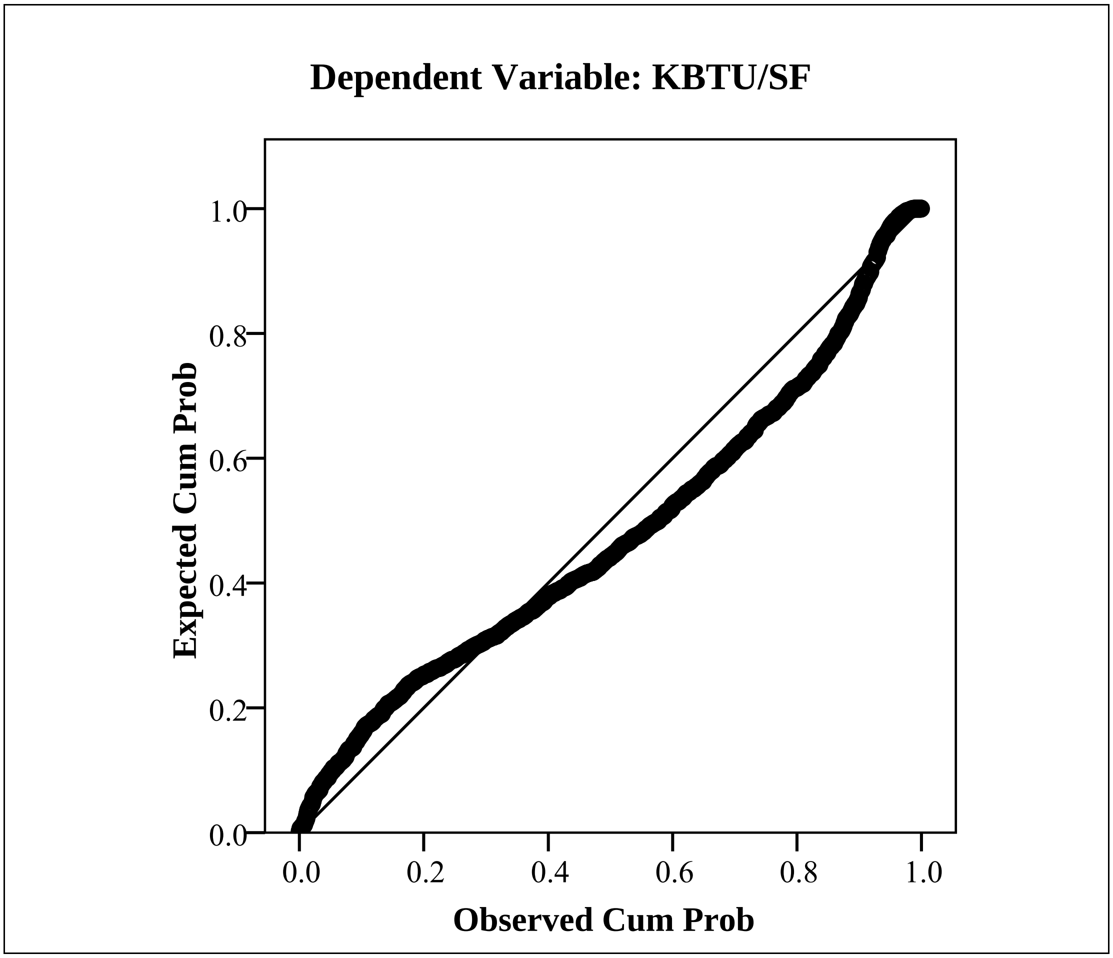


Figure 4-12. Normal P-P Plot of Regression Standardized Residual

In addition to the above tests for normal distribution and constant variance, the correlation or independence of the random error terms was investigated. In time series data analysis such as conducted in this thesis effort, error terms are commonly positively correlated. This autocorrelation is typically caused by the omission of one or many key independent variables, which forces the error terms to include the missing variable effects seen in the model (Kutner et al., 2004). SPSS 15.0 for Windows calculated a Durbin-

Watson statistic value of 0.532. Since this value is less than 2, indications reflect positive autocorrelation is present. Thus, the variance in the error terms may be understated, the true standard deviation of the estimated regression coefficient may be understated, and confidence intervals and tests using the *t*- and *F* distributions may not be strictly applicable (Kutner et al., 2004). The presence of positive autocorrelation could create misleading results. The two principle techniques for correcting for autocorrelation are to add one or more predictor variables to the model or to use transformed variables; however, neither technique was used in this research effort.

After verifying the assumptions of the random error term, two analyses were conducted to investigate for statistical outliers and influential data points. Standardized residual data was analyzed, which resulted in 1.5 percent of the residuals occurring beyond three standard deviations. Each of the outlier data points were analyzed, but were kept in the data set since their values were very close to three standard deviations. A check for influential data points was also conducted. The Cook's distance measure produced results that ranged between 0.000 and 0.141. The maximum value of 0.141 was not significantly large, so no influential data points were detected.

The next step in model validation included testing for the existence of multicollinearity. SPSS 15.0 for Windows calculated variance inflation factors (VIF) ranging from 1.077 to 5.117 for the independent variables as shown in Table 4-2. Since no VIF values were greater than ten, multicollinearity was not present; thus, each regression coefficient was stable, indicating the independent variables correlate with the dependent variable and not with each other.

The remaining statistical test was the analysis of the adjusted multiple coefficient of determination, R^2, value. The R^2 value for the final model was 0.814, which indicated a good fit. This means that when every independent variable was considered, the model explains 81.4 percent of the variability in the data. The *p*-values displayed in Table 4-2 indicate that the independent variables were all statistically significant since each value is less than 0.05. The constant regression coefficient, β_0, corresponds to the non-climatic sensitivity load. When climate-related variables are not impacting energy consumption, the base electrical load, such as lighting or appliance support, is represented by β_0. In this model, 37.903 KBTU/SF was the estimated non-climatic energy consumption per square foot load. During the stepwise regression process, several of the independent variables were automatically discarded through its iterations in developing the best model. The following independent variables remained in the model: HDD, CDD, HDD * WS, AFMC, USAFE, Climate Zone 2, Climate Zone 3, Non-Combat Flying mission, and Strategic/ISR mission. Thus, WS, RH, HDD * RH, CDD * WS, CDD * RH, HDD * CDD, and WS * RH were all deemed not statistically significant. Therefore, the only influential weather parameters proved to be heating degree-days, cooling degree-days, and wind speed. Relative humidity was determined to be not statistically significant. These results compare favorably to existing research. Additionally, AETC, AMC, PACAF, and AFSPC were not significant, which implies that energy consumption per square foot in these major commands was similar to that of ACC, the base case. Similarly, Climate Zone 4 and Climate Zone 5 were not significant, which implies that energy consumption per square foot in these climate zones was similar to that of Climate

Zone 1, the base case. Finally, the Support mission was not significant, implying its energy consumption per square foot was similar to the Combat Flying mission. All the remaining dummy variables included in the model were significant and had either negative or positive coefficients, which showed its tendency towards energy consumption per square foot when compared to its respective base case. For example, Climate Zones 2 and 3 both had negative coefficients. This showed that less energy per square foot was consumed in these two climate zones than in Climate Zone 1.

The ultimate test for the final regression model was analyzing its ability to predict energy consumption. Recall that one fiscal year's worth of data (2006) was set aside for final testing of the model. Determining the percentage difference between the actual and predicted values provided a measure of the model's performance. Overall, the percentage difference average was 20.14 percent with a range of 0.61 to 62.05 percent. Of the 76 installations, 23 percent had a percentage differential of less than 10 percent. Of those installations with a differential of less than 10 percent, 58 percent were from Climate Zone 5. Most surprisingly, of the 16 installations with a percentage differential in excess of 30 percent, 81.3 percent were of the Combat Flying mission category. Additionally, three of the five installations within Climate Zone 1 had percentage differentials in excess of 30 percent. The complete results are provided in Appendix B. While the overall results were less than desirable, the model still can be useful in providing insight to energy policy makers regarding the significant influence weather conditions have on energy consumption.

Trend Analysis Results

Graphical methods were utilized to determine which months were best and worst in terms of energy consumption. Monthly data, shown in Figure 4-13, were plotted through the period of October 1985 to September 2006 to determine whether trending can be predicted. As the graph depicts, the greatest expenditure of energy occurred in January, while the least expenditure occurred in June (closely followed by September). These results were expected in that May/June and September/October are traditionally transition months in which installations are shifting between heating and cooling demands. Commonly, the heating and cooling loads are minimal during this transitional period when the outside air temperature is the closest to the base or reference temperature, T_b, as discussed in Chapter II. Figure 4-14 provides supporting evidence of this conjecture as May/June and September/October have the lowest mean totals of HDD and CDD of any other months. Of particular note, the results clearly showed a significant difference in energy consumption between the winter and summer months. This discovery could lead to potentially drastic changes in current energy conservation efforts, providing support to focus efforts on heating system improvements versus cooling system initiatives.

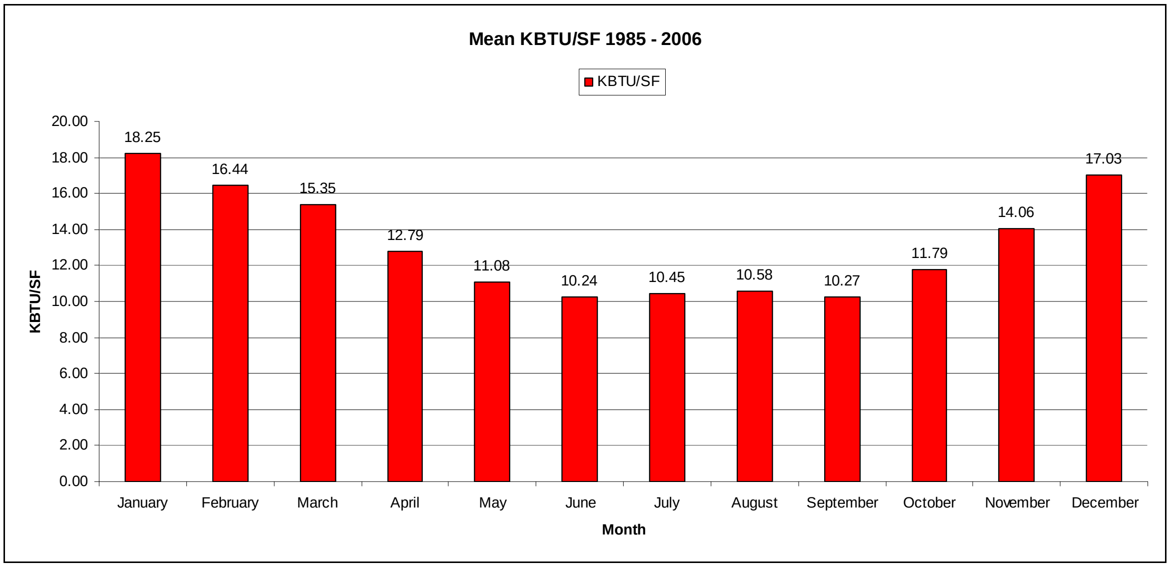


Figure 4-13. 1985 to 2006 Mean KBTU/SF Values

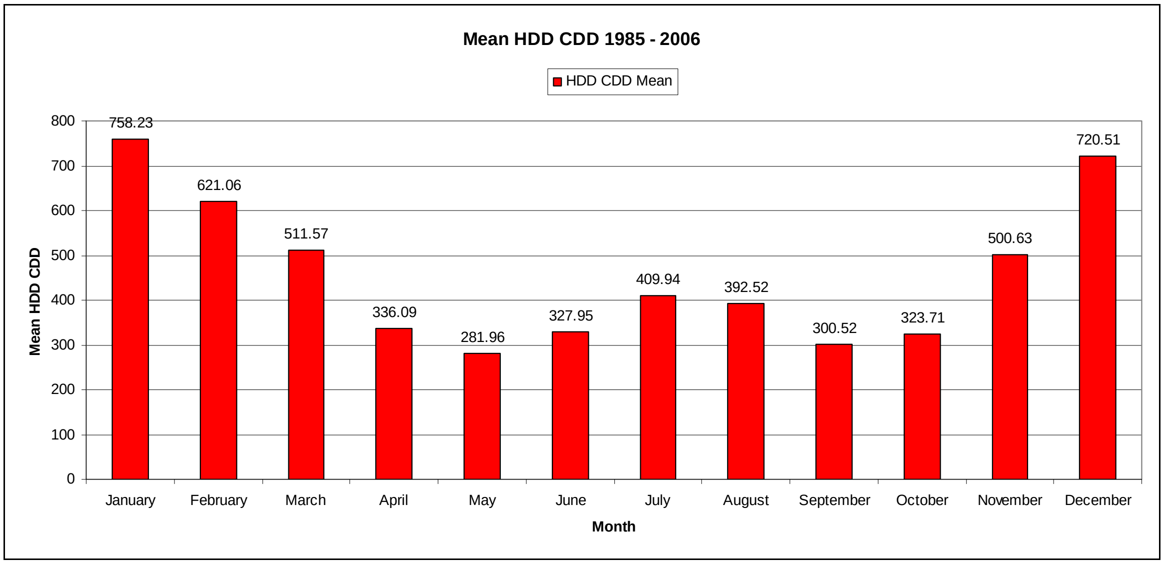


Figure 4-14. 1985 to 2006 Mean HDD + CDD Values

Graphical methods were again utilized to determine which energy source (electricity, natural gas, or other) varied the most between winter and summer months. Recall from Chapter II that electricity and natural gas were selected for analysis since these two energy sources account for approximately 80 percent of all annual facility energy consumed on Air Force installations; thus, gaining insight into energy source expenditures throughout the year can assist in developing energy initiative programs. Several graphs were produced that display energy source consumption averages for each installation. January and August were selected since natural gas and electricity use were greatest in each month, respectively. To capture the results of the analysis of each month, the differential was also plotted. Figure 4-15 provides a sample of the plots by individual base, grouped by climate zone. Each plot is listed in Appendix C. Five additional plots were created to assess each climate zone's combined energy use. Figure 4-16 shows the average KBTU/SF per energy source for Climate Zone 1. All five climate zone plots are provided in Appendix D.

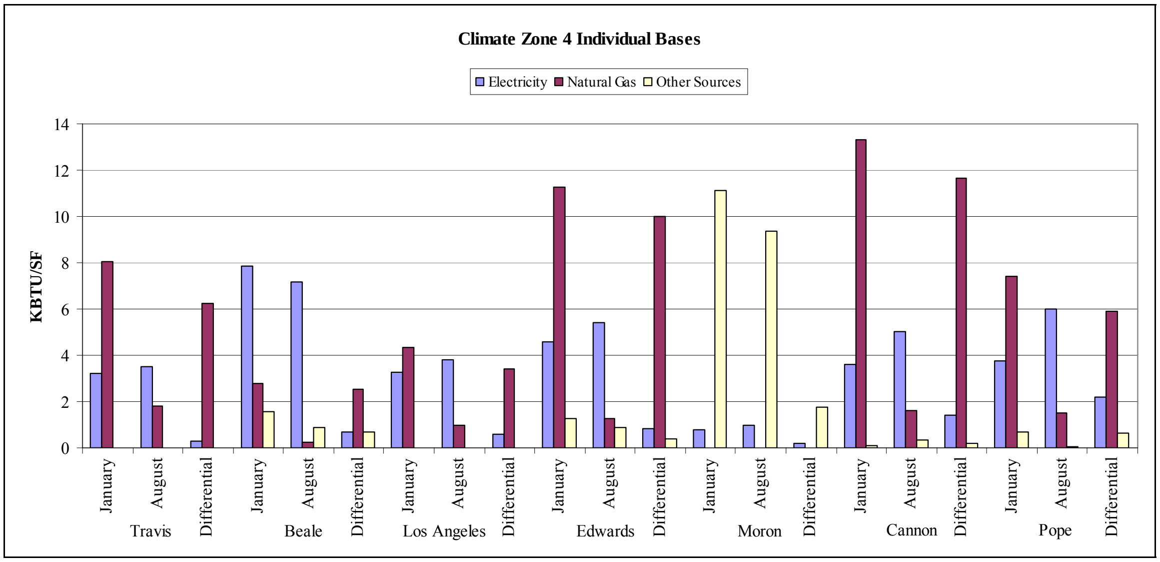


Figure 4-15. Energy Source Consumption per Base for Climate Zone 4

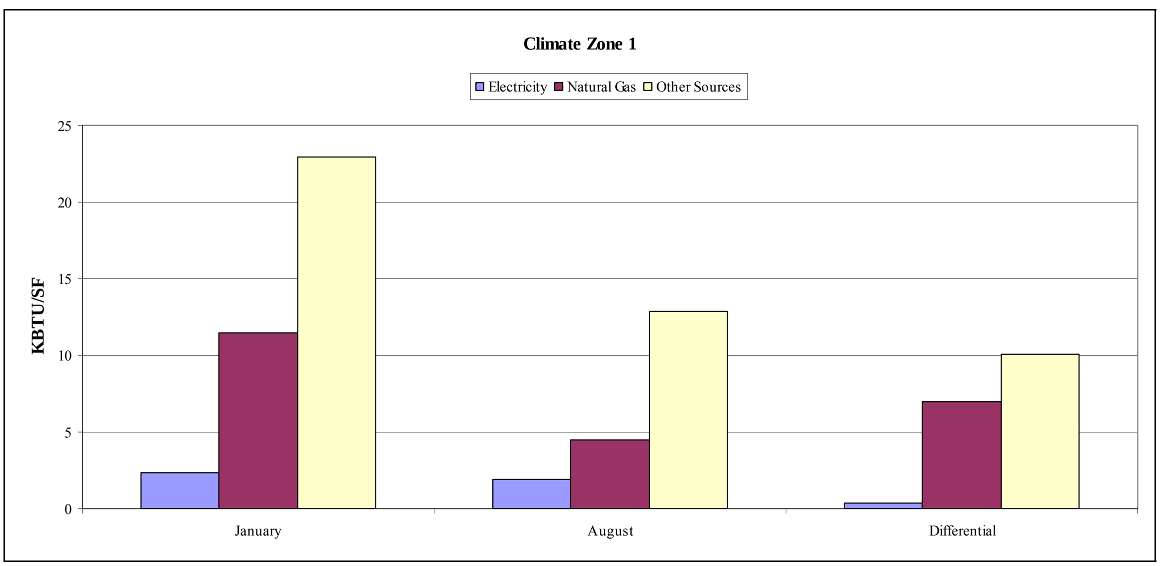


Figure 4-16. Energy Source Consumption for Climate Zone 1

Both Figures 4-15 and 4-16, supported by the remaining plots in Appendices C and D, provided substantial evidence that the natural gas differential far exceeded the electricity differential, allowing insight into future energy reduction initiatives. Of note, the "other" energy sources' differentials exceeded the electricity differential in four of five climate zone plots and the natural gas differential in two of five plots. This was expected since the two predominant energy sources comprising the "other" category were fuel oil and coal, primarily used during the heating season. Thus, natural gas and other fuel sources used during the heating season create a greater opportunity for energy reduction by reducing energy consumption during that time period. Additionally, electricity consumption remained relatively stable during both the heating and cooling seasons, especially in the colder climate areas (Climate Zones 1, 2, and 3). This indicated that the majority of the electricity utilized was for non-heating and non-cooling purposes.

Summary

This chapter provided a summary of the results of analyzing the weather and energy consumption data obtained from AFCESA and AFCCC through the use of multiple linear regression in an effort to create a useable model to predict energy consumption at Air Force installations. Numerous diagnostic tests were performed to assess the applicability of the developed regression model. Although the resulting model revealed evidence of possible positive autocorrelation commonly observed in time series data, it still provided proof of the significant influence weather has on energy consumption and further supported empirical literature in this endeavor. Additionally, the variables selected proved to explain 81.4 percent of the variability in energy consumption per square foot, as seen in the resulting R^2 value of 0.814.

Insight was also gained into energy consumption trends on Air Force installations. Transitional periods involving shifts between heating and cooling seasons commonly called for the lowest energy demand throughout the year. Additionally, natural gas and other energy sources used during the heating season varied significantly when compared to the corresponding cooling season. Electricity consumption remained relatively constant when supporting cooling and heating seasons. Through observations made regarding these trends, installations can engage in energy conservation efforts that target those mechanical systems utilized during peak demand periods.

Chapter V. Discussion and Conclusions

This chapter provides a review of the research questions and a short summary of the associated findings. The key results and implications of this thesis effort are addressed, limitations associated with the predictive energy consumption model are identified, and recommendations for future uses of the model are provided. Additionally, this chapter provides future research topics that may assist in developing a more robust energy model that captures additional variations in energy consumption.

Discussion of Results

Three research questions were identified in Chapter I: (1) What type of variation does weather impose on energy consumption at Air Force installations? (2) Which months are best/worst in terms of energy consumption? and (3) Which energy sources vary the greatest between the heating and cooling seasons? The analysis detailed in the preceding chapters was intended to address each research objective. The regression model, along with each variable, is discussed in the following paragraphs, along with implications to future energy policies based on trending results.

Regression Analysis Results

The final regression model included nine independent variables (three quantitative weather variables and six dummy variables) that proved to have a significant relationship with energy consumption at Air Force installations. Recalling the first research question regarding how weather impacts energy consumption, the energy model highlighted the importance of outdoor air temperature (in the form of heating and cooling degree-days) and wind speed (in the form of an interaction variable). According to Mirasgedis et al. (2006), “demand forecasts are direct functions of weather and other variables” (p. 221). Therefore, any changes in the variables (heating degree-days, cooling degree-days, and the interaction variable of heating degree-days and wind speed) affect the energy consumption to the degree of their regression coefficient values. Of the three, heating degree-days had the strongest influence on energy consumption, accounting for over 68 percent of the variation in energy consumption in terms of contribution to the R^2 value. The interaction variable accounted for 1.4 percent, while cooling degree-days accounted for less than 1 percent. This result reinforces the assertions in existing literature that outdoor air temperature has the most impact on energy consumption. Two conjectures can help account for the overwhelming significance of heating degree-days in the regression model. First, as depicted in Figure 4-13 and Figure 4-14, winter months’ energy consumption rates and HDD/CDD mean totals far exceed those values observed in the summer months. This indicates that throughout the year, heating requirements outweigh cooling requirements, thus increasing its relative influence in predicting energy consumption. Second, temperature variances resulting from daily mean temperatures diverging from the reference temperature of 65 degrees Fahrenheit (18.3 degrees Celsius) occur more frequently and in greater quantity for heating degree-days than cooling degree-days. Put another way, more heating degree-days are generated since temperatures throughout the year, on average, are more frequently below 65 degrees Fahrenheit and at greater ranges than cooling degree-days are above 65 degrees

Fahrenheit. In contrast to heating and cooling degree-days, wind speed and relative humidity individually were not statistically significant to the model, which was a surprising finding since the literature indicated that both weather conditions had proven predictive in other studies.

Of those weather conditions that were statistically significant, the regression coefficient was 0.032 for heating degree-days, -0.001 for the interaction variable, and 0.007 for cooling degree-days. This means for a one unit increase in heating degree-days, the energy consumption per square foot increases by 0.032 when all other variables are held constant. The fact that the regression coefficient for heating degree-days is positive is not surprising. As air temperatures drop below the reference temperature of 65 degrees Fahrenheit and associated heating degree-days begin to accumulate, energy consumption increases as heating systems are activated. For the heating degree-days and wind speed interaction variable, its regression coefficient was negative 0.001, which indicates that for one unit increase of this variable, energy consumption per square foot decreases by 0.001, when all other variables remain constant. This result was unexpected, especially since the heating degree-day component was included in the interaction term. However, since the regression coefficient was so small, the overall impact was essentially negligible. Cooling degree-days have a slightly larger impact on energy consumption than the interaction term with a regression coefficient of 0.007. Again, this result was expected using the same logic as with heating degree-days. Interestingly, though, was the relative magnitude difference of the regression coefficient of HDD when compared to the CDD coefficient. The HDD coefficient was over 4.5

times larger than the CDD coefficient, providing further supporting evidence that heating degree-days and its associated heating energy load requirement far exceeds that of cooling requirements. Put another way, one unit increase of HDD has over 4.5 times the impact on energy consumption than one unit increase of CDD.

The addition of dummy variables further refined the model and provided a mechanism to draw conclusions regarding energy consumption. Of the qualitative variables, several variables within the major command, climate zone, and mission categories significantly impacted the energy consumption values for the installations. As previously discussed, ACC, Climate Zone 1, and the Combat Flying mission were the base cases for the regression model. Thus, when interpreting the remaining variables, their contributions to the dependent variable are compared to those of the base case variables. For example, the regression coefficient for Climate Zone 2 was -38.671, which indicates that installations included in Climate Zone 2 use 38.671 KBTU/SF less energy than those installations in Climate Zone 1. Similarly, installations that are part of AFMC use 39.897 KBTU/SF more energy than ACC installations. Installations within AFMC, USAFE, Climate Zone 2, Climate Zone 3, Non-Combat Flying, or Strategic/ISR categories each had more or less energy consumption rates when compared to ACC, Climate Zone 1, or Combat Flying, respectively, in the amount equivalent to their regression coefficients. Overall, location, in terms of major command and climate, and mission categories played varying roles in energy consumption per square footage when applied to the final model.

The final regression model did not produce expected results in terms of categories, however. For example, the model indicated installations within Climate Zones 1, 4, and 5 had similar energy consumption per square foot rates, while installations within Climate Zones 2 and 3 used less energy on average when compared to the other three. Since Climate Zone 1 has the greatest heating requirement of all climate zones, the expectation was that the remaining four climate zones would each have increasing negative regression coefficients, with Climate Zone 5 (smallest heating requirement) having the largest negative coefficient.

Another anomaly is seen in the MAJCOM category. Only AFMC and USAFE returned different energy consumption rates when compared to ACC and the remaining MAJCOMs. An explanation for this difference could be made for installations in USAFE, since construction standards utilized in those countries are markedly different than those used in the United States and could account for the consumption rate variances. However, using this argument would support varying rates for PACAF installations located in Korea, Japan, and Guam as well; yet the PACAF category proved to be not statistically significant to the model. Additionally, AFMC installations are not distinctly different in construction standards than other installations located in the United States, thus again invalidating this conjecture.

Regarding the mission category, the results were also mixed. Non-Combat Flying installations were shown to use less energy than Combat Flying installations while Strategic/ISR installations proved to use more. Support installations, however, used comparable rates to Combat Flying installations. Assuming that installations within the

Combat Flying category conduct standard operations on weekends and routinely after duty hours (before 0800 hours and after 1700 hours), it would be expected that mission categories with less working time would expend less energy. This is confirmed by the fact that Non-Combat Flying installations returned a negative regression coefficient. However, Support category installations did not conform to this logic. Additionally, Strategic/ISR mission installations used more energy than Combat Flying installations, which could be attributed to the significant energy consumption required in round-the-clock satellite and ICBM monitoring and other specialty missions.

Trend Analysis Results

Two key insights are provided through the trend analysis conducted to determine which months were best/worst in terms of energy consumption and which energy sources varied the greatest between the heating and cooling seasons. First, the winter months use the most energy than any other seasonal periods, with January having the highest consumption rate. This fact should be seriously considered by energy managers when developing energy initiatives and used for justification for proper allocation of scarce financial resources. Heating system upgrades would provide the greatest opportunities to reduce an installation's energy consumption rate, thus assisting in meeting federal energy reduction goals. Second, natural gas, coal, and fuel oil are the three predominant energy sources used to meet the heating demands as shown in Appendix C. The differentials between energy sources and months shown in those graphs indicate that the greatest opportunity to reduce energy lies in developing initiatives affecting natural gas, coal, and fuel oil consumption during winter months. Again, this data is invaluable in developing programs to affect the greatest impact on energy reduction.

Limitations

Numerous limitations apply to this thesis effort. First, the energy consumption data obtained are only available in monthly increments. If weekly, hourly, or daily data were made available, a more robust model could have been created to address various factors, such as weekends, holidays, non-peak daily energy loads, or weekly energy fluctuations. Secondly, the usefulness of the regression model is driven by the accuracy of the data involved in its creation. This thesis effort relied upon the accuracy of the information provided by AFCESA (pulled from DUERS) and AFCCC. The DUERS data are manually inputted by installation energy managers, thus subject to human error. Attempts were made to correct inaccuracies that were found; however, it is likely that inaccurate data impacted the model. Third, by using time series data, the resulting model is subjected to positive autocorrelation. This could potentially lead to the creation of inaccurate regression coefficients. Fourth, establishment of an overarching energy consumption baseline that would represent the entire Air Force usage is difficult to determine. Finally, the scope of this study limits the total variance explained by the regression model. By focusing primarily on weather parameters, other factors such as building construction standards, population, or facility age are not addressed.

Recommendations

Despite the fact that the model produced less than desired predictive abilities when used to compare fiscal year 2006 data, this research effort still highlights the significant influence weather conditions impart on energy consumption. Air Force energy policy makers and base energy managers can use this analysis to develop policies and programs that target systems that consume the most energy on Air Force installations. By focusing on initiatives that improve heating systems and its associated infrastructure, the greatest gain in energy conservation can be achieved. Air Force energy policy makers can make informed decisions on where energy funds should be spent throughout the Air Force, thereby meeting federal energy reduction goals. Decision makers can additionally assess the potential impact of weather anomalies or suspected climate changes on energy consumption and adjust current directives or policies to compensate for those impacts, such as revising design standards in federal facilities to reflect temperature-related energy use.

Future Research

Several research avenues exist that could improve upon the results of this thesis. First, the DUERS data could be dissected and analyzed in various other methods. For each Air Force installation, energy consumption data is reported separately into two categories: industrial and military family housing. Since the data is reported in two distinct economic sectors (commercial and residential), future research could involve creating individual models for each sector. Especially in today's environment of increasing housing privatization, insight could be gained on the impact of eliminating the residential sector from the overall energy consumption total and how federally mandated energy reduction goals are affected. Future research could answer the question on which economic sector is more energy efficient. In addition to economic sectors, energy sources are also reported separately in DUERS. Future research could entail focusing on one energy source and creating a separate prediction model based solely on its consumption.

Secondly, the existing model could be revised to include additional variables, such as a baseline non-climatic energy load, an "energy reduction" factor that captures an overall annual energy reduction value per year, installation age, mean facility age, or various qualitative dummy variables addressing weekends, holidays, or other less energy-intensive periods. Adding variables that address improved construction methods or periods of inactivity could possibly account for additional variations in energy consumption. Additional research could then be undertaken to determine the progress of older bases in attaining federally mandated energy goals.

Third, the population could be increased to incorporate all Reserve and Guard installations for regression analysis, thereby enabling the creation of one overarching Air Force model or three separate models. Analysis and comparison of trends in Reserve and Guard installations to active duty bases could present currently unforeseen energy reduction opportunities. By adding additional installations, an intra-state analysis could be conducted to determine variances within installations located in the same state.

Finally, an analysis to compare northern tier versus southern tier bases could be accomplished. As shown in this research effort, bases with traditionally more heating requirements have differing energy requirements than those with more cooling requirements. Regression models could be created to capture this difference to more accurately reflect energy consumption rates.

Conclusion

This thesis provided an analysis of climate-based variables and their impact on energy consumption at Air Force installations. Since the early 1970s, energy consumption has been an increasing concern, in terms of both our nation's security and budget. Legislation has been passed over the last three decades to encourage energy conservation in federal facilities; however, the impact that weather conditions impart on those energy reduction efforts continues to be lacking. Understanding these external factors relating to energy use and creating a robust energy model would provide a mechanism for leaders to more accurately measure conservation efforts and assist in the development of more effective energy reduction programs. Revelations gained through trend analysis provide opportunities for improvements to existing energy programs, all focusing on meeting federally mandated energy reduction goals.

Appendix A: Installations and Associated Categories

BASE	MAJCOM	Climate Zone	Mission	Base Type
Altus AFB	AETC	5	Non-Combat Flying	Major
Andersen AFB	PACAF	5	Support	Major
Andrews AFB	AMC	3	Non-Combat Flying	Major
Arnold AFB	AFMC	4	Support	Major
Aviano AB	USAFE	3	Combat Flying	Major
Barksdale AFB	ACC	5	Combat Flying	Major
Beale AFB	ACC	4	Combat Flying	Major
Bolling AFB	AETC**	3	Support	Major
Cannon AFB	ACC	4	Combat Flying	Major
Cape Canaveral AFS	AFSPC	5	Strategic/ISR	Major
Charleston AFB	AMC	5	Combat Flying	Major
Cheyenne Mountain AS	AFSPC	2	Strategic/ISR	Minor
Columbus AFB	AETC	5	Non-Combat Flying	Major
Davis-Monthan AFB	ACC	5	Combat Flying	Major
Dover AFB	AMC	3	Combat Flying	Major
Dyess AFB	ACC	5	Combat Flying	Major
Edwards AFB	AFMC	4	Support	Major
Eglin AFB	AFMC	5	Combat Flying	Major
Eielson AFB	PACAF	1	Combat Flying	Major
Ellsworth AFB	ACC	2	Combat Flying	Major
Elmendorf AFB	PACAF	1	Combat Flying	Major
Fairchild AFB	AMC	2	Combat Flying	Major
Falcon AFB	AFSPC	2	Strategic/ISR	Major
FE Warren AFB	AFSPC	2	Strategic/ISR	Major
Grand Forks AFB	AMC	1	Combat Flying	Major
Hanscom AFB	AFMC	3	Support	Major
Hickam AFB	PACAF	5	Support	Major
Hill AFB	AFMC	2	Combat Flying	Major
Holloman AFB	ACC	4	Combat Flying	Major
Hurlburt Field	ACC*	5	Combat Flying	Major
Incirlik AB	USAFE	5	Support	Major
Kadena AB	PACAF	5	Combat Flying	Major
Keesler AFB	AETC	5	Support	Major
Kirtland AFB	AFMC	4	Combat Flying	Major
Kunsan AB	PACAF	3	Combat Flying	Major
Lackland AFB	AETC	5	Support	Major

BASE	MAJCOM	Climate Zone	Mission	Base Type
Lajes Field	USAFE	4	Support	Major
Lakenheath AB	USAFE	3	Combat Flying	Major
Langley AFB	ACC	4	Combat Flying	Major
Laughlin AFB	AETC	5	Non-Combat Flying	Major
Little Rock AFB	AETC	5	Non-Combat Flying	Major
Los Angeles AFB	AFSPC	4	Support	Major
Luke AFB	AETC	5	Non-Combat Flying	Major
MacDill AFB	AMC	5	Combat Flying	Major
Malmstrom AFB	AFSPC	2	Strategic/ISR	Major
Maxwell AFB	AETC	5	Support	Major
McChord AFB	AMC	3	Combat Flying	Major
McConnell AFB	AMC	3	Combat Flying	Major
McGuire AFB	AMC	3	Combat Flying	Major
Mildenhall AB	USAFE	3	Combat Flying	Major
Minot AFB	ACC	1	Combat Flying	Major
Misawa AB	PACAF	2	Combat Flying	Major
Moody AFB	ACC*	5	Combat Flying	Major
Moron AB	USAFE	4	Combat Flying	Minor
Mountain Home AFB	ACC	3	Combat Flying	Major
Nellis AFB	ACC	5	Combat Flying	Major
New Boston AFS	AFSPC	2	Strategic/ISR	Minor
Offutt AFB	ACC	2	Non-Combat Flying	Major
Osan AB	PACAF	3	Combat Flying	Major
Patrick AFB	AFSPC	5	Strategic/ISR	Major
Peterson AFB	AFSPC	2	Strategic/ISR	Major
Pope AFB	AMC	4	Combat Flying	Major
Ramstein AB	USAFE	2	Non-Combat Flying	Major
Randolph AFB	AETC	5	Non-Combat Flying	Major
Robins AFB	AFMC	5	Non-Combat Flying	Major
Scott AFB	AMC	3	Non-Combat Flying	Major
Seymour Johnson AFB	ACC	5	Combat Flying	Major
Shaw AFB	ACC	5	Combat Flying	Major
Sheppard AFB	AETC	5	Non-Combat Flying	Major
Spangdahlem AB	USAFE	2	Combat Flying	Major
Thule AB	AFSPC	1	Strategic/ISR	Minor
Tinker AFB	AFMC	4	Combat Flying	Major
Travis AFB	AMC	4	Combat Flying	Major
Tyndall AFB	AETC	5	Non-Combat Flying	Major

BASE	MAJCOM	Climate Zone	Mission	Base Type
United States Air Force Academy	AETC***	2	Support	Major
Vance AFB	AETC	5	Non-Combat Flying	Major
Vandenberg AFB	AFSPC	4	Strategic/ISR	Major
Whiteman AFB	ACC	3	Combat Flying	Major
Wright Patterson AFB	AFMC	3	Support	Major
Yokota AB	PACAF	4	Non-Combat Flying	Major

***** - Hurlburt and Moody are AFSOC bases, but recoded to ACC bases due to similar missions.

****** - Bolling is an AFDW base, but recoded to AETC due to similar mission.

******* - United States Air Force Academy is a Direct Reporting Unit, but recoded to AETC due to similar mission.

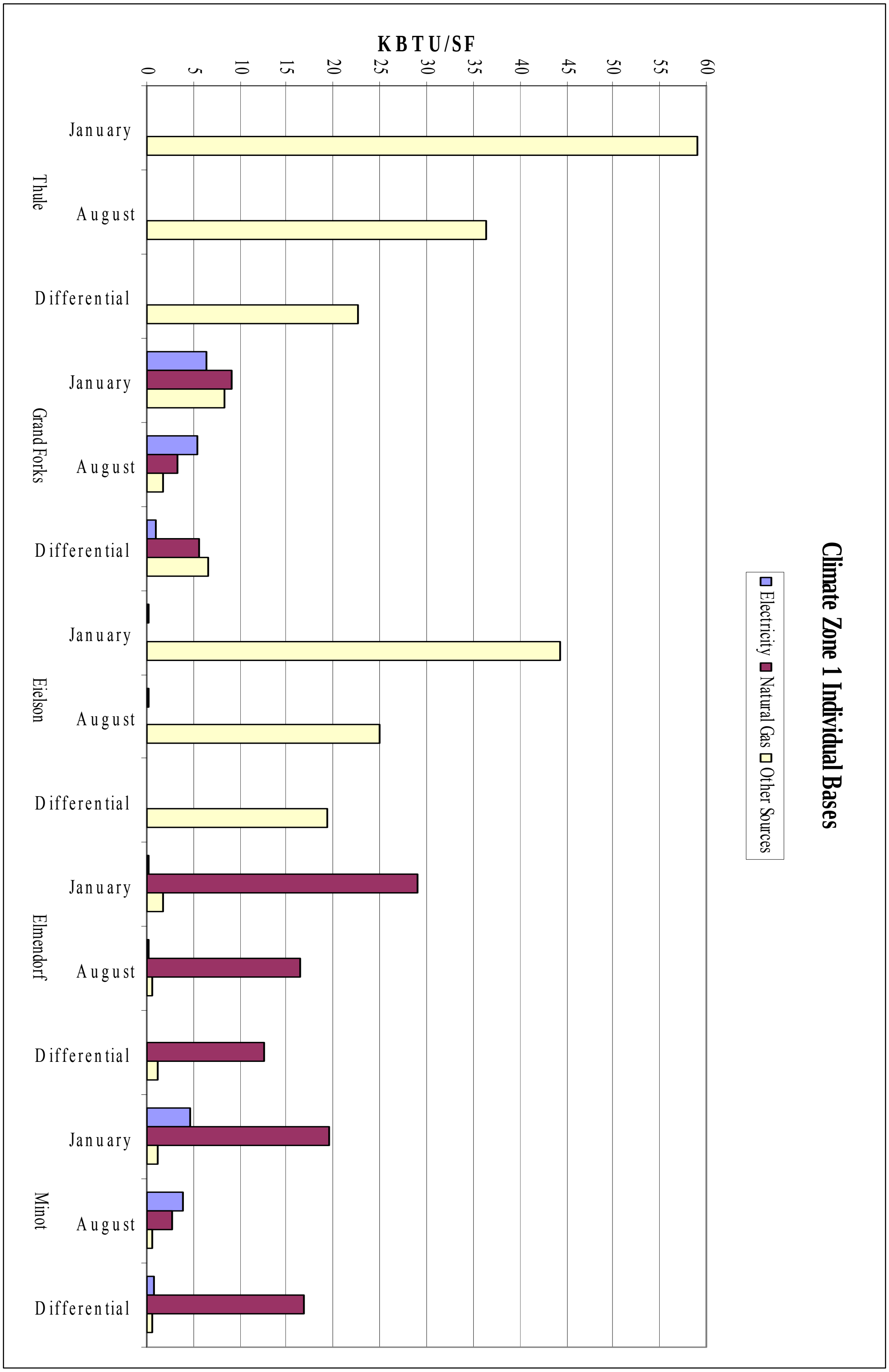
Appendix B: Comparison of Actual Energy Consumption versus Model Prediction

BASE	Actual KBTU/SF	Model KBTU/SF	Percent Difference
Altus AFB	85.12	116.22	26.76
Andersen AFB	71.27	81.28	12.31
Andrews AFB	80.81	116.05	30.37
Aviano AB	71.65	98.68	27.39
Barksdale AFB	85.79	102.33	16.17
Beale AFB	87.44	107.82	18.91
Bolling AFB	124.01	119.74	3.56
Cannon AFB	99.10	122.12	18.85
Charleston AFB	95.37	98.13	2.82
Columbus AFB	86.06	114.04	24.54
Davis-Monthan AFB	79.43	90.40	12.13
Dover AFB	162.39	121.60	33.54
Dyess AFB	102.89	101.87	1.00
Edwards AFB	118.76	160.68	26.09
Eglin AFB	106.33	131.42	19.09
Eielson AFB	359.86	428.84	16.09
Ellsworth AFB	101.57	139.83	27.37
Elmendorf AFB	120.36	317.16	62.05
Fairchild AFB	110.80	162.24	31.70
Falcon AFB	219.83	169.16	29.96
FE Warren AFB	138.04	172.06	19.77
Grand Forks AFB	144.32	237.19	39.15
Hickam AFB	59.19	69.33	14.63
Hill AFB	177.68	184.89	3.90
Holloman AFB	86.57	112.84	23.28
Hurlburt Field	99.23	89.84	10.46
Incirlik AB	62.17	83.98	25.97
Kadena AB	62.24	71.25	12.66
Keesler AFB	77.84	89.82	13.34
Kirtland AFB	100.18	172.01	41.76
Kunsan AB	104.45	148.97	29.89
Lackland AFB	83.58	87.54	4.52
Lakenheath AB	101.29	84.05	20.51
Langley AFB	107.01	123.10	13.07
Laughlin AFB	75.77	84.62	10.45

BASE	Actual KBTU/SF	Model KBTU/SF	Percent Difference
Little Rock AFB	94.01	117.77	20.17
Los Angeles AFB	69.99	73.06	4.20
Luke AFB	72.14	87.41	17.46
MacDill AFB	98.48	74.85	31.56
Malmstrom AFB	132.81	170.46	22.09
Maxwell AFB	109.68	105.33	4.13
McChord AFB	117.36	147.98	20.69
McConnell AFB	85.52	116.86	26.82
McGuire AFB	148.71	137.70	8.00
Mildenhall AB	109.64	121.53	9.79
Minot AFB	139.24	212.93	34.61
Misawa AB	159.50	140.50	13.52
Moody AFB	99.06	93.61	5.82
Moron AB	52.59	79.84	34.13
Mountain Home AFB	111.12	159.53	30.35
Nellis AFB	96.35	111.72	13.76
Offutt AFB	144.75	130.36	11.04
Osan AB	111.33	177.55	37.30
Patrick AFB	61.39	107.67	42.99
Peterson AFB	157.10	169.16	7.13
Pope AFB	81.57	124.97	34.73
Ramstein AB	68.22	135.02	49.47
Randolph AFB	84.16	83.66	0.61
Robins AFB	125.95	143.84	12.44
Scott AFB	113.75	130.70	12.97
Seymour Johnson AFB	79.90	119.04	32.88
Shaw AFB	79.11	111.27	28.91
Sheppard AFB	82.29	98.77	16.69
Spangdahlem AB	66.75	128.74	48.15
Thule AB	448.99	541.18	17.04
Tinker AFB	194.34	157.91	23.07
Travis AFB	71.86	100.02	28.15
Tyndall AFB	85.26	80.62	5.76
United States Air Force Academy	117.56	145.12	18.99
Vance AFB	92.32	120.43	23.34
Vandenberg AFB	175.00	138.61	26.25
Whiteman AFB	158.02	126.15	25.26

BASE	Actual KBTU/SF	Model KBTU/SF	Percent Difference
Wright Patterson AFB	184.86	193.72	4.57
Yokota AB	148.52	143.85	3.25
Overall Results			20.14

Appendix C: Energy Source Plots for Each Climate Zone and Installation


Climate Zone 1 Individual Bases
Electricity
Natural Gas
Other Sources
KBTU/SF
0
5
10
15
20
25
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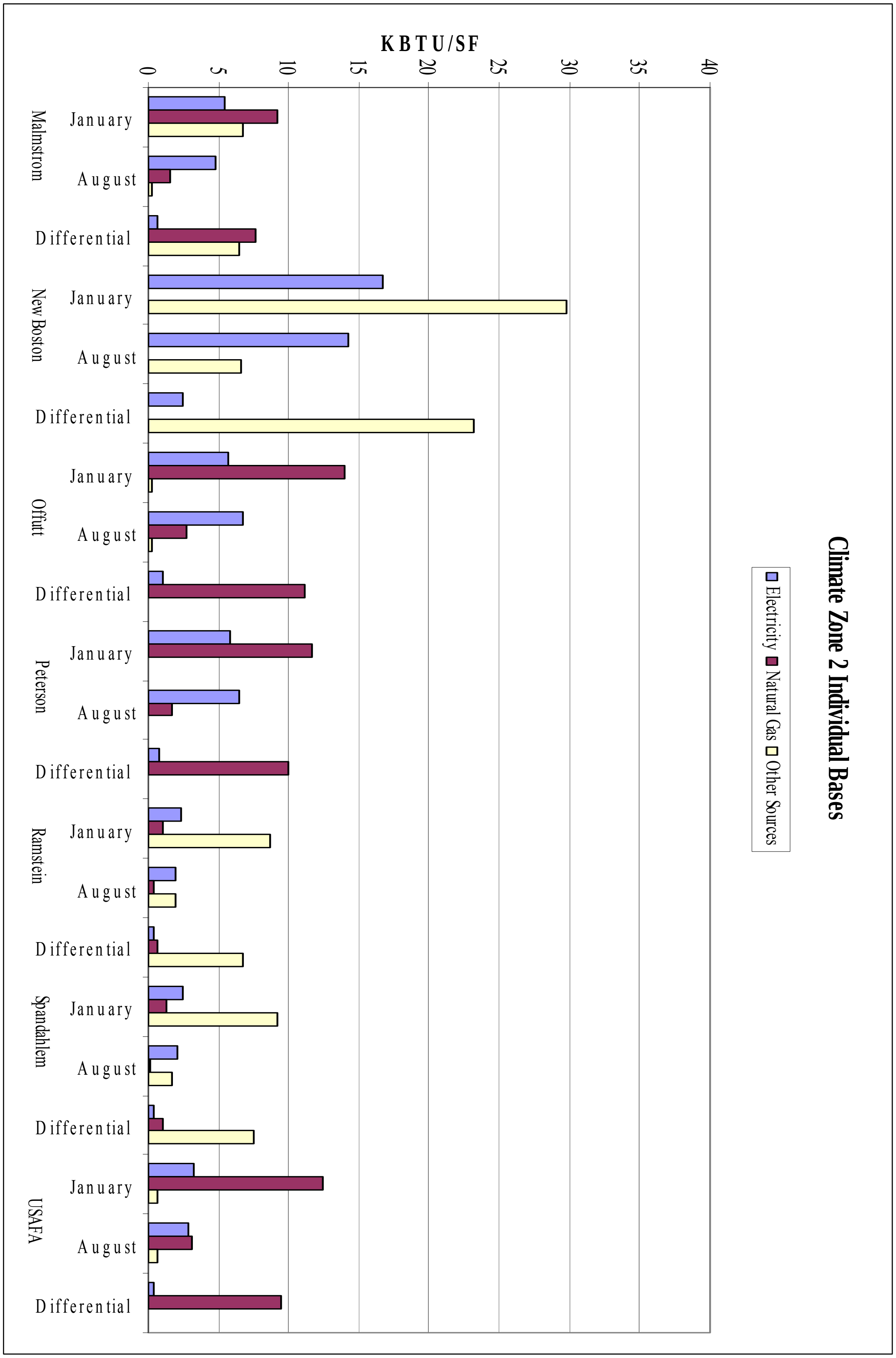
40
45
50
55
60
Thule
Grand Forks
Eielson
Elmendorf
Minot
January
August
Differential


Climate Zone 2 Individual Bases
Electricity
Natural Gas
Other Sources
KBTU/SF
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5
10
15
20
25
30
35
40
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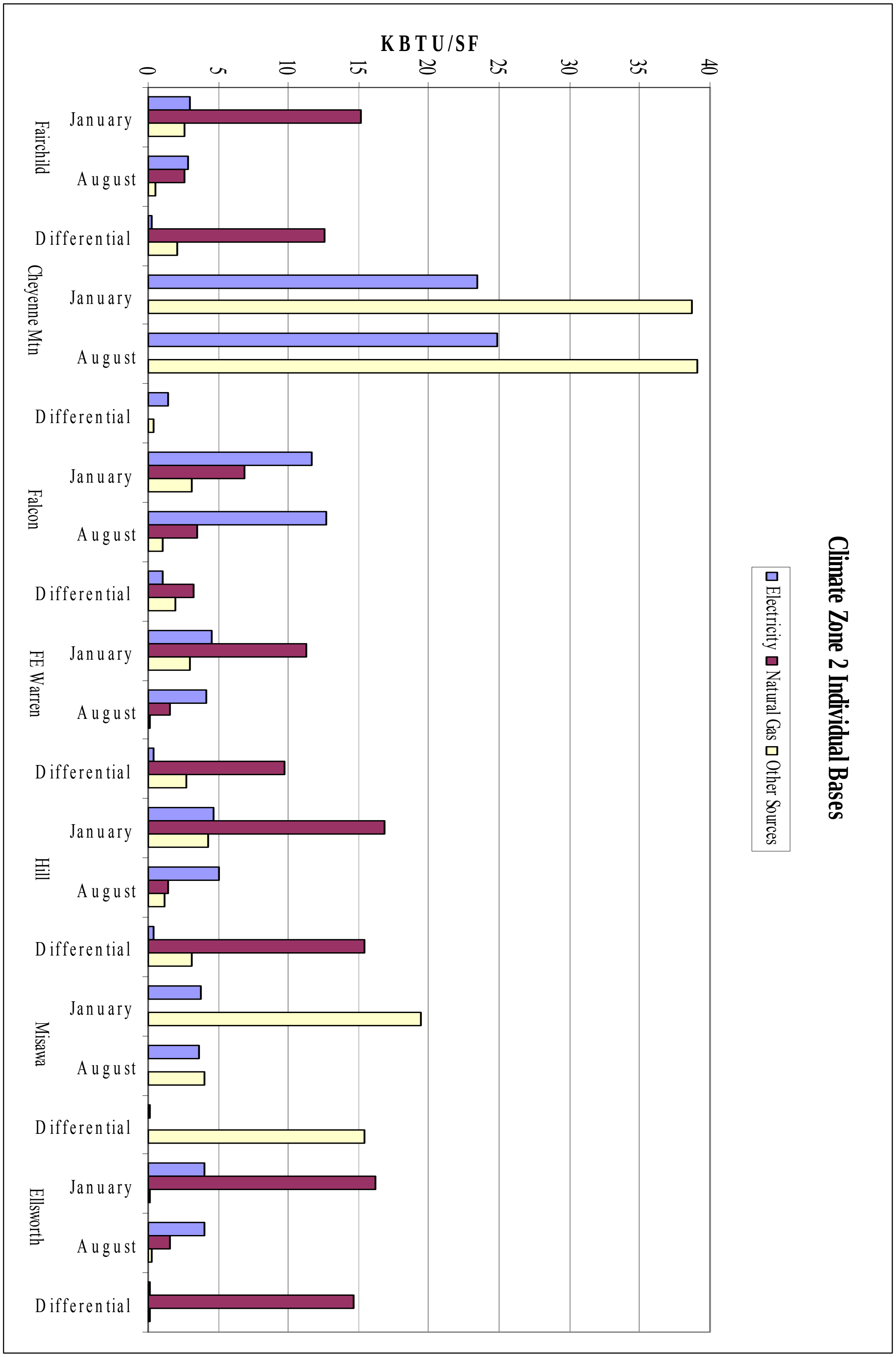
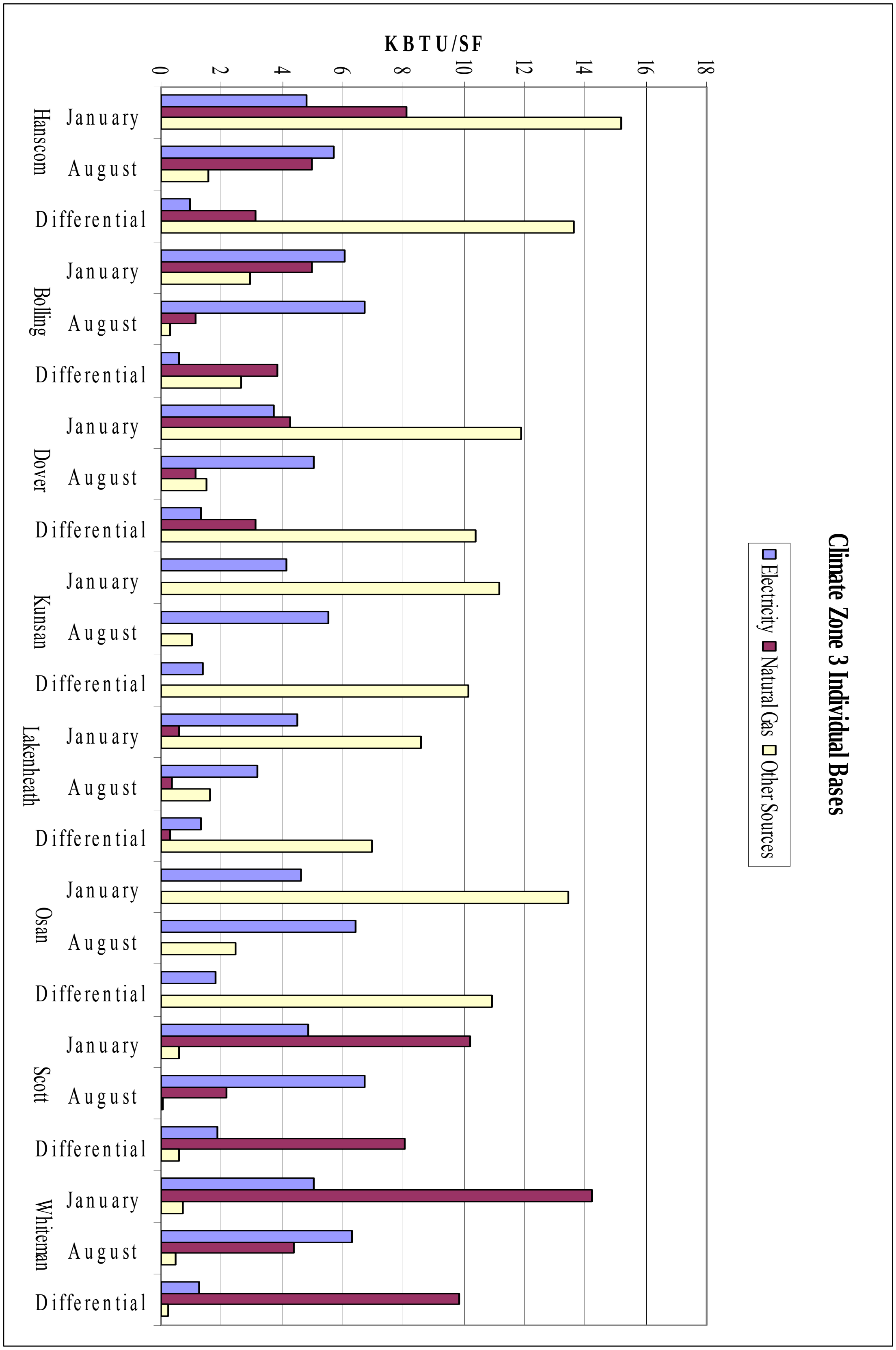
Offutt
Peterson
Ramstein
Spandahlem
USAFA
January
August
Differential


Climate Zone 2 Individual Bases
Electricity
Natural Gas
Other Sources
KBTU/SF
0
5
10
15
20
25
30
35
40
Fairchild
Cheyenne Mtn
Falcon
FE Warren
Hill
Misawa
Ellsworth
January
August
Differential


Climate Zone 3 Individual Bases
Electricity
Natural Gas
Other Sources
KBTU/SF
0
2
4
6
8
10
12
14
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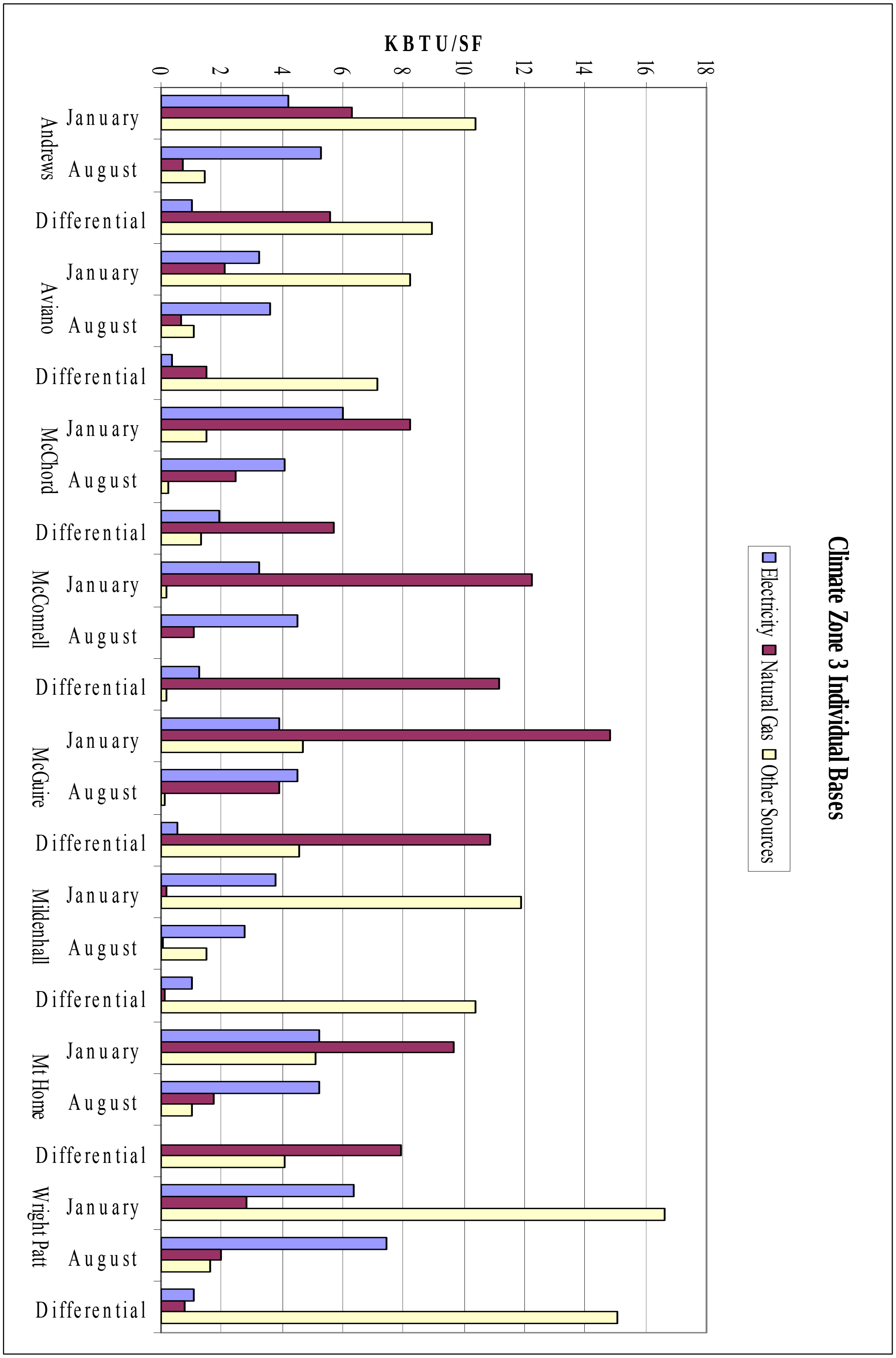
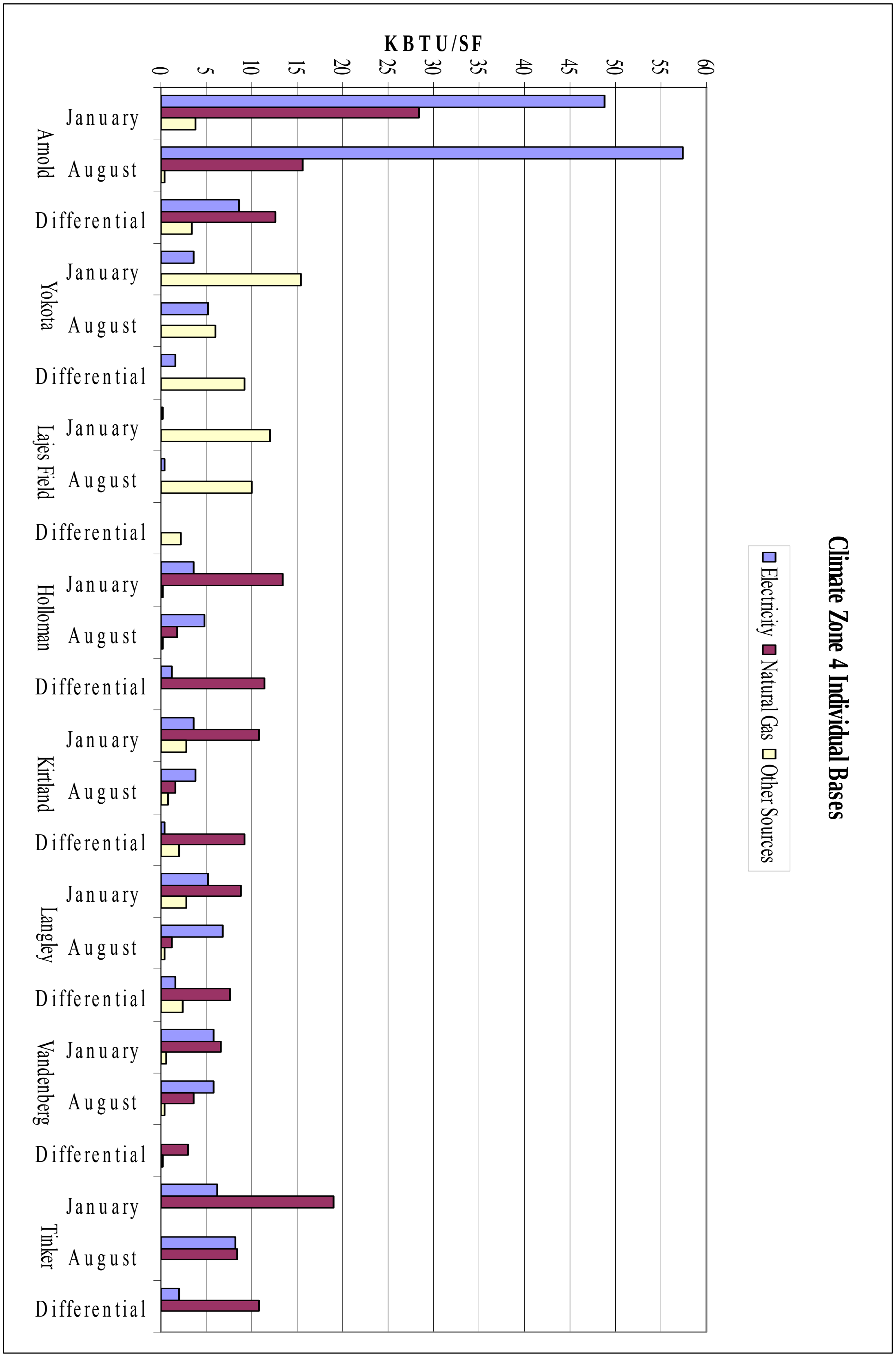
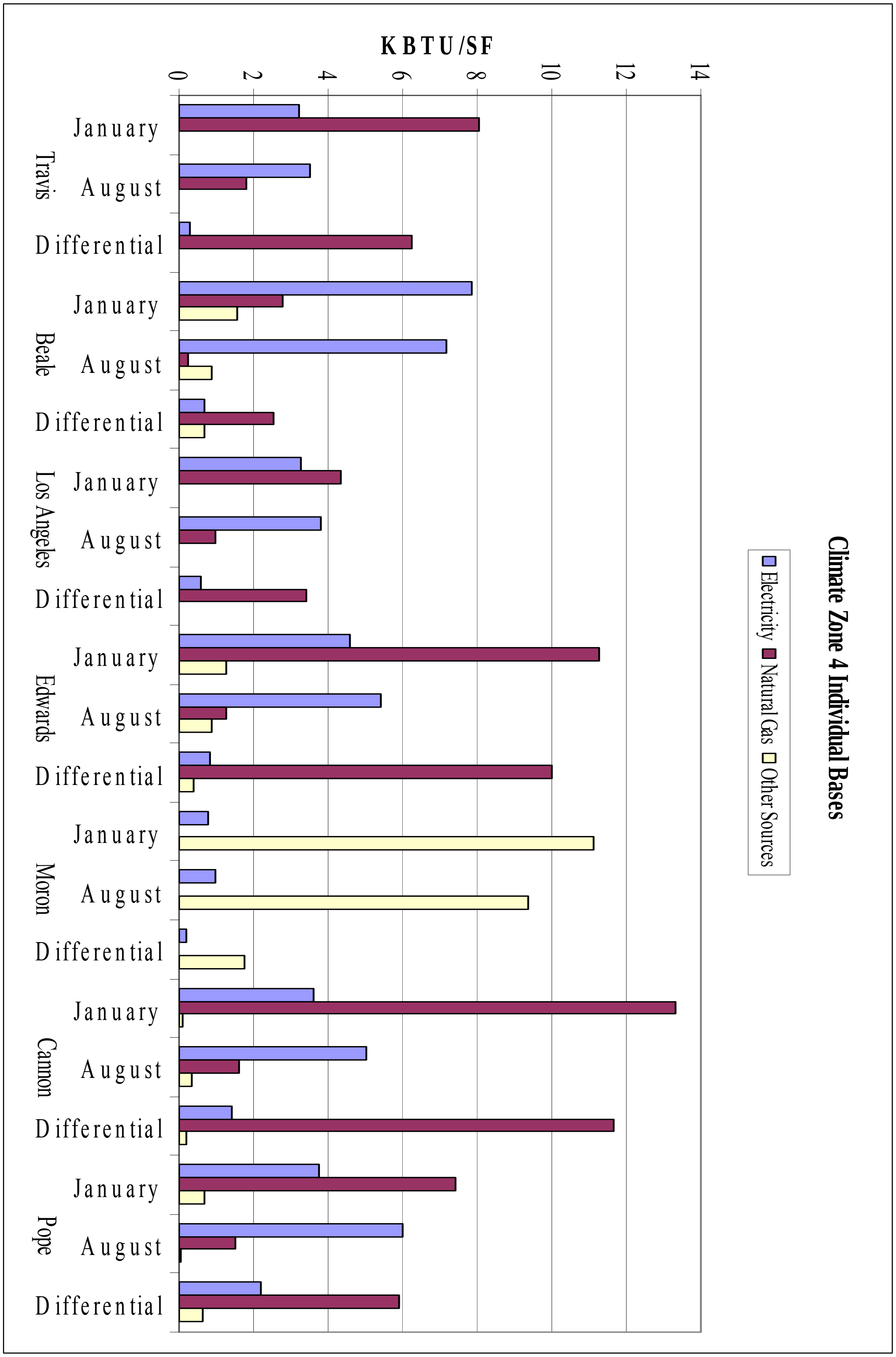
Hanscom
Bolling
Dover
Kunsan
Lakenheath
Osan
Scott
Whiteman
January
August
Differential



Climate Zone 3 Individual Bases
Electricity
Natural Gas
Other Sources
KBTU/SF
0
2
4
6
8
10
12
14
16
18
Andrews
Aviano
McChord
McConnell
McGuire
Mildenhall
Mt Home
Wright Patt
January
August
Differential


Climate Zone 4 Individual Bases
Electricity
Natural Gas
Other Sources
KBTU/SF
0
5
10
15
20
25
30
35
40
45
50
55
60
January
August
Differential
Arnold
Yokota
Lajes Field
Holloman
Kirtland
Langley
Vandenberg
Tinker


Climate Zone 4 Individual Bases
Electricity
Natural Gas
Other Sources
KBTU/SF
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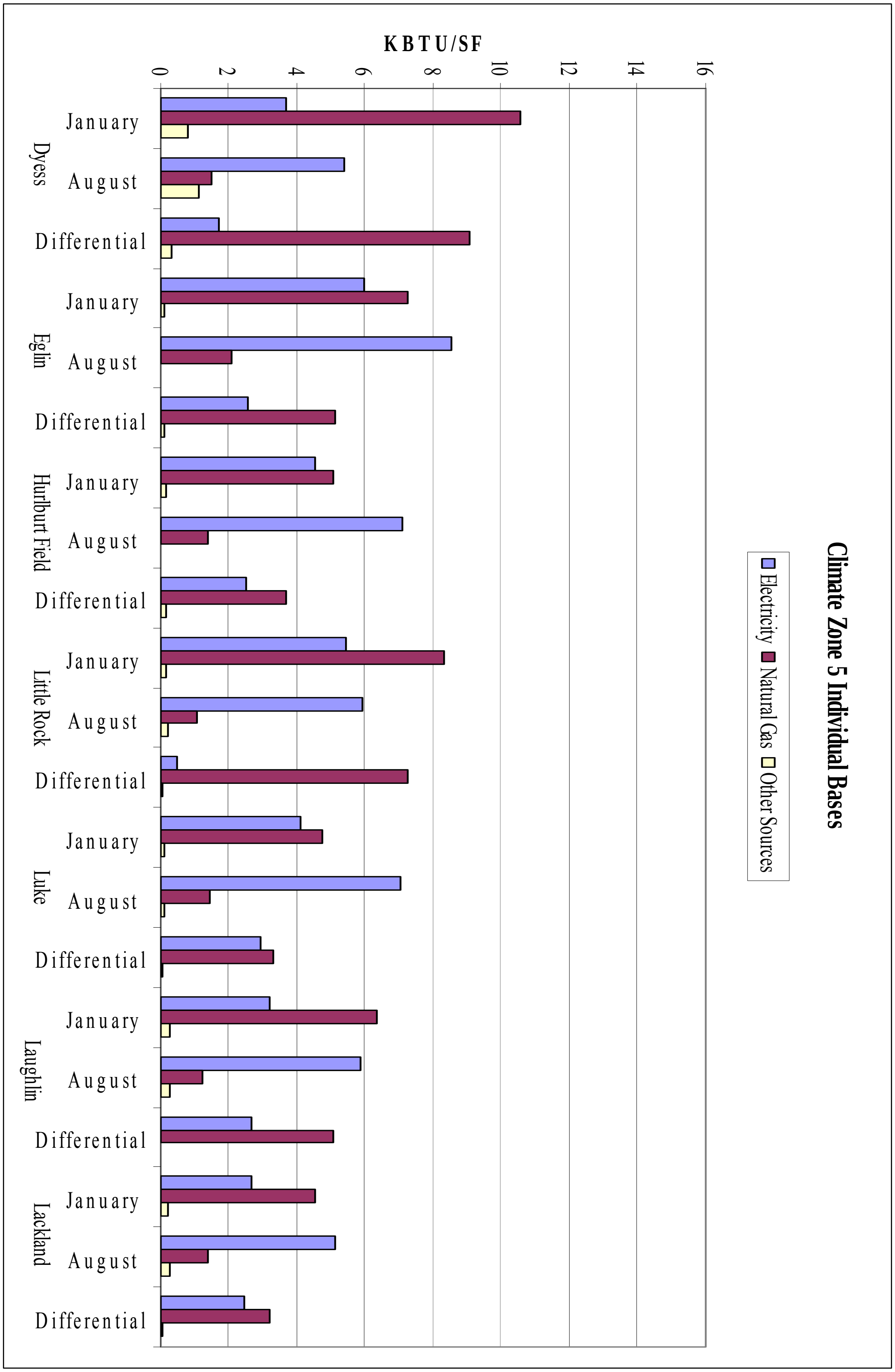
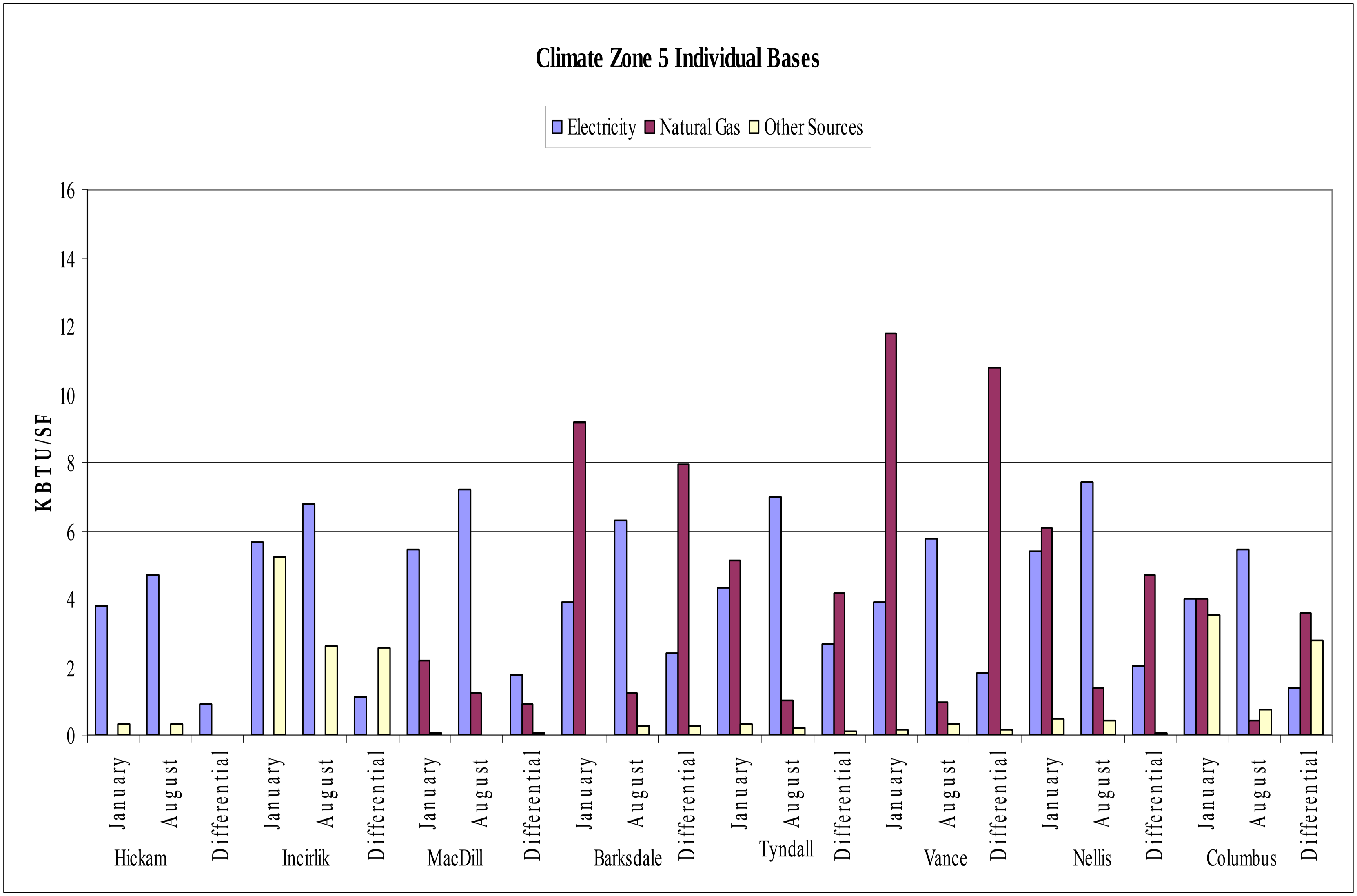
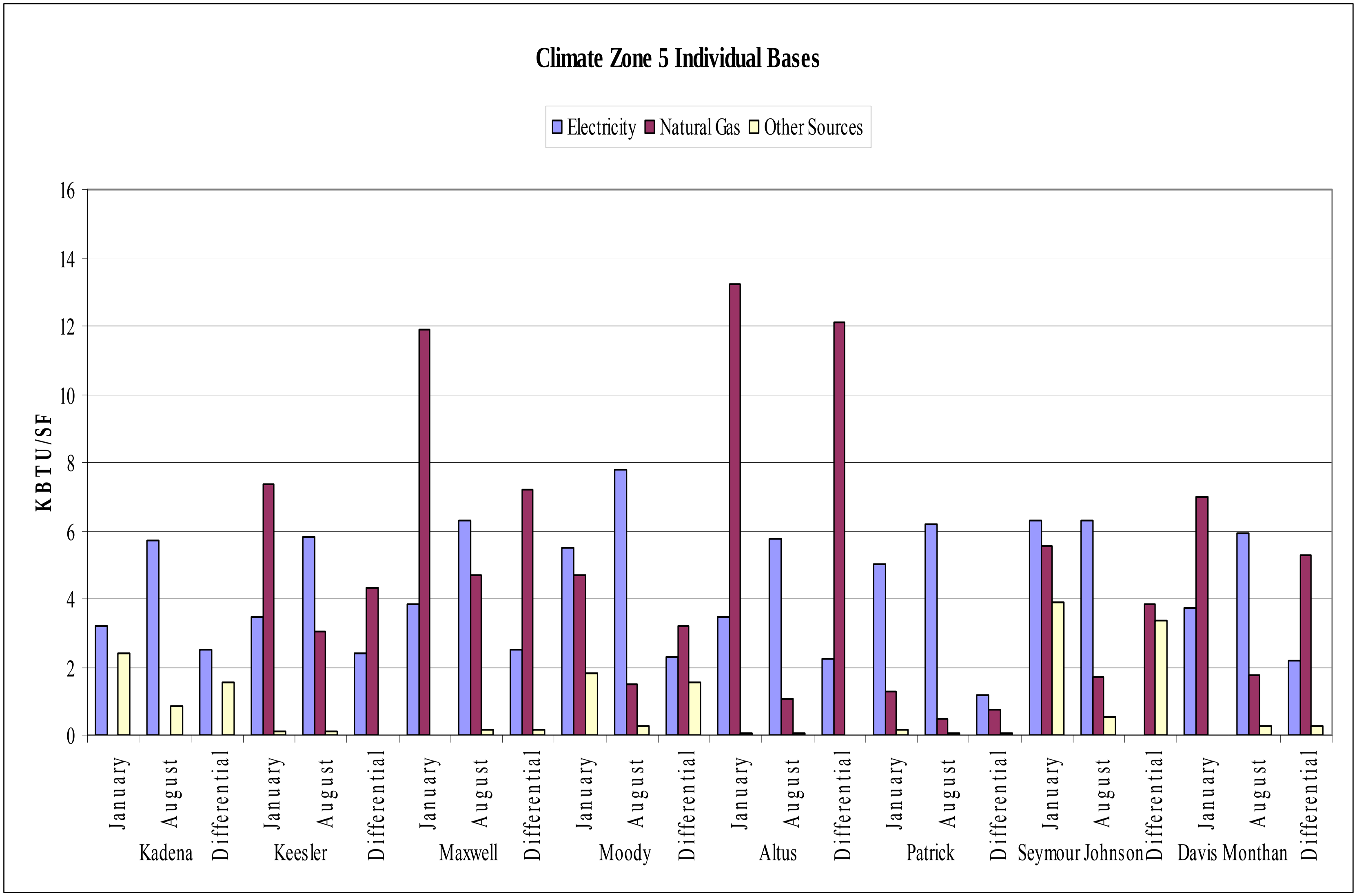
2
4
6
8
10
12
14
Travis
Beale
Los Angeles
Edwards
Moron
Cannon
Pope
January
August
Differential

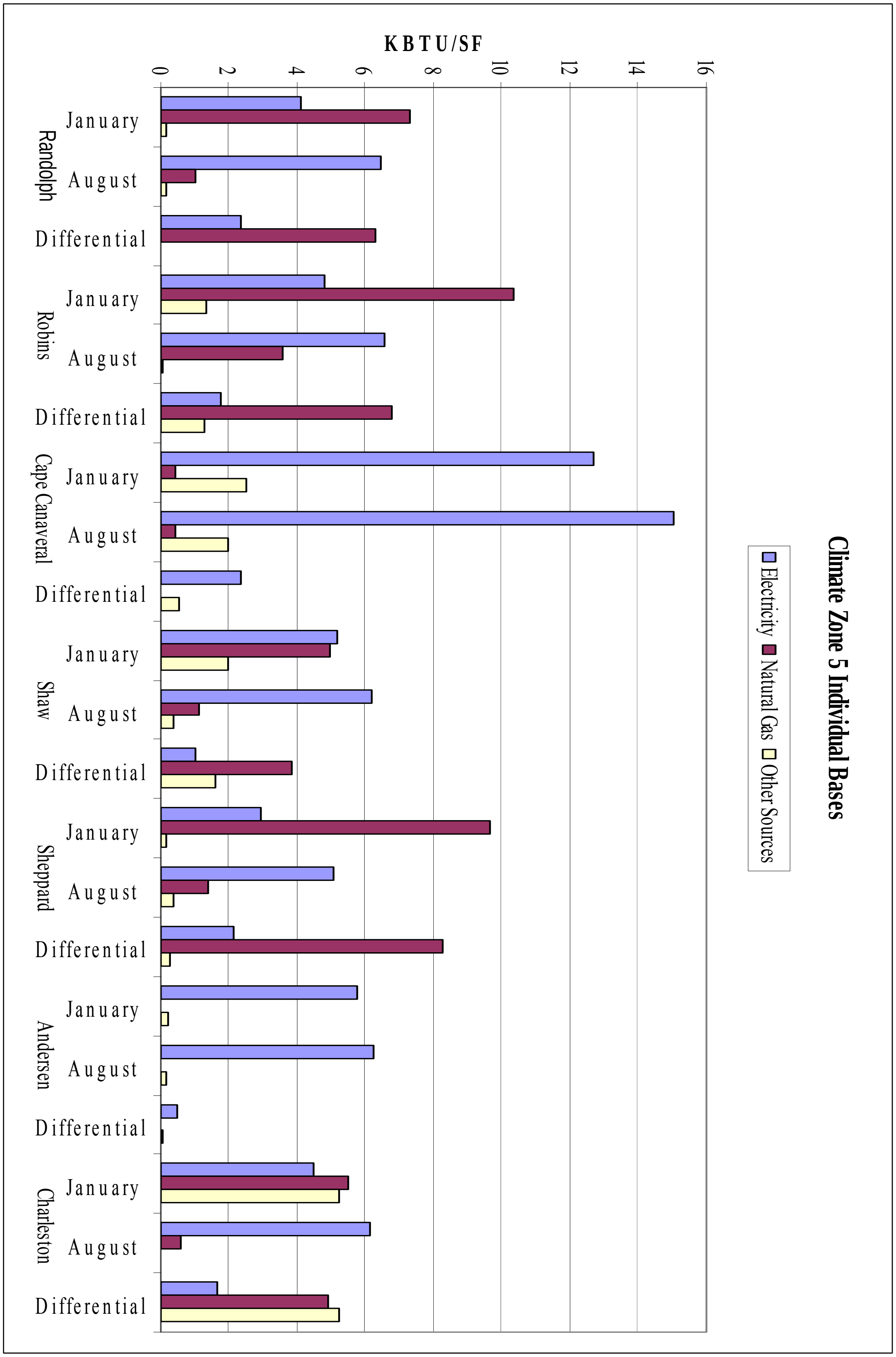

Climate Zone 5 Individual Bases
Electricity
Natural Gas
Other Sources
KBTU/SF
0
2
4
6
8
10
12
14
16
January
August
Differential
Dyess
Eglin
Hurlburt Field
Little Rock
Luke
Laughlin
Lackland



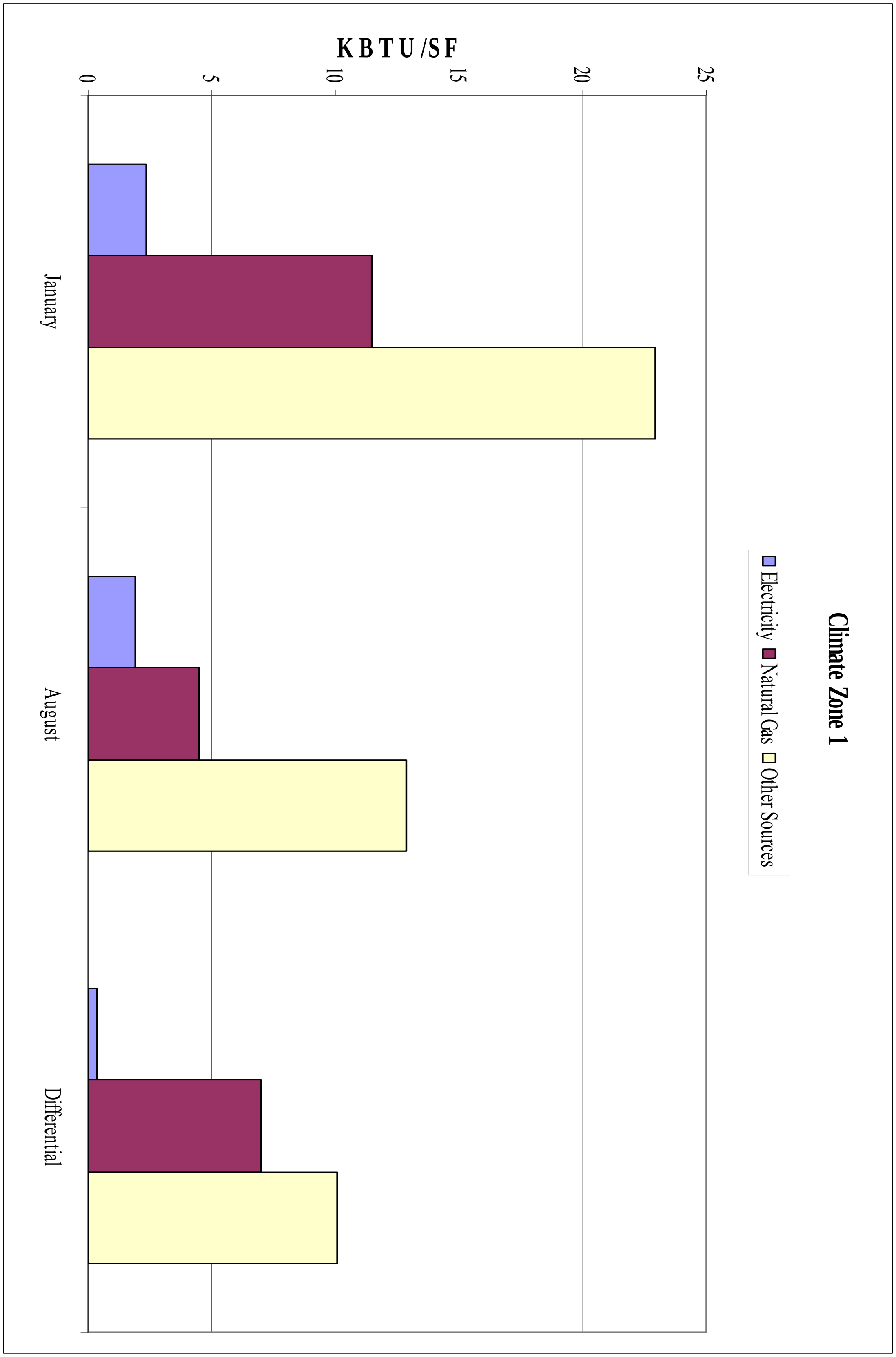
Climate Zone 5 Individual Bases
Electricity
Natural Gas
Other Sources
KBTU/SF
0
2
4
6
8
10
12
14
16
January
August
Differential
Hickam
Incirlik
MacDill
Barksdale
Tyndall
Vance
Nellis
Columbus



Climate Zone 5 Individual Bases
Electricity
Natural Gas
Other Sources
KBTU/SF
0
2
4
6
8
10
12
14
16
January
August
Differential
Kadena
Keesler
Maxwell
Moody
Altus
Patrick
Seymour Johnson
Davis Monthan


Climate Zone 5 Individual Bases
Electricity
Natural Gas
Other Sources
KBTU/SF
0
2
4
6
8
10
12
14
16
Randolph
Robins
Cape Canaveral
Shaw
Sheppard
Andersen
Charleston
January
August
Differential

Appendix D: Energy Source Plots for Each Climate Zone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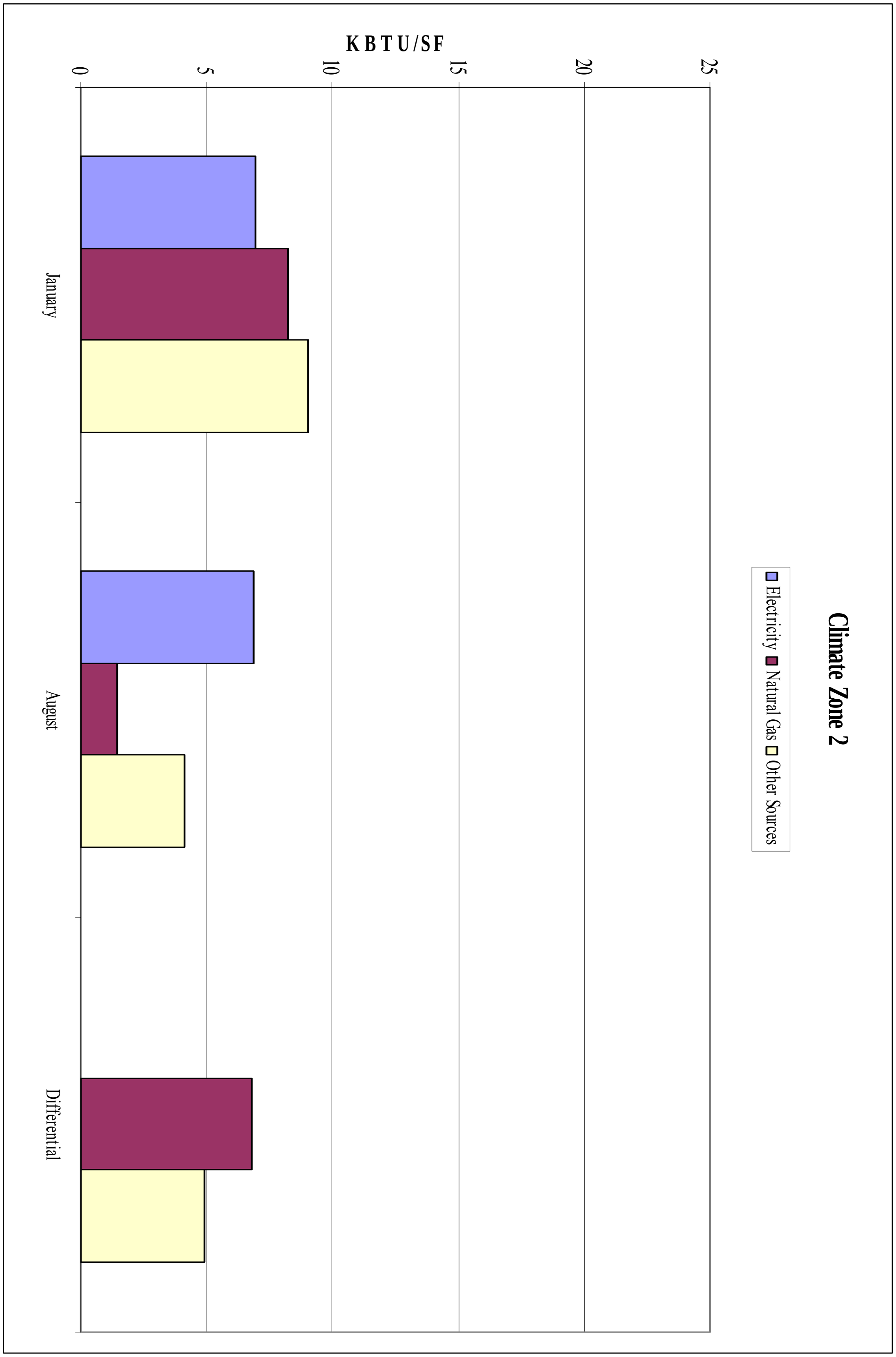
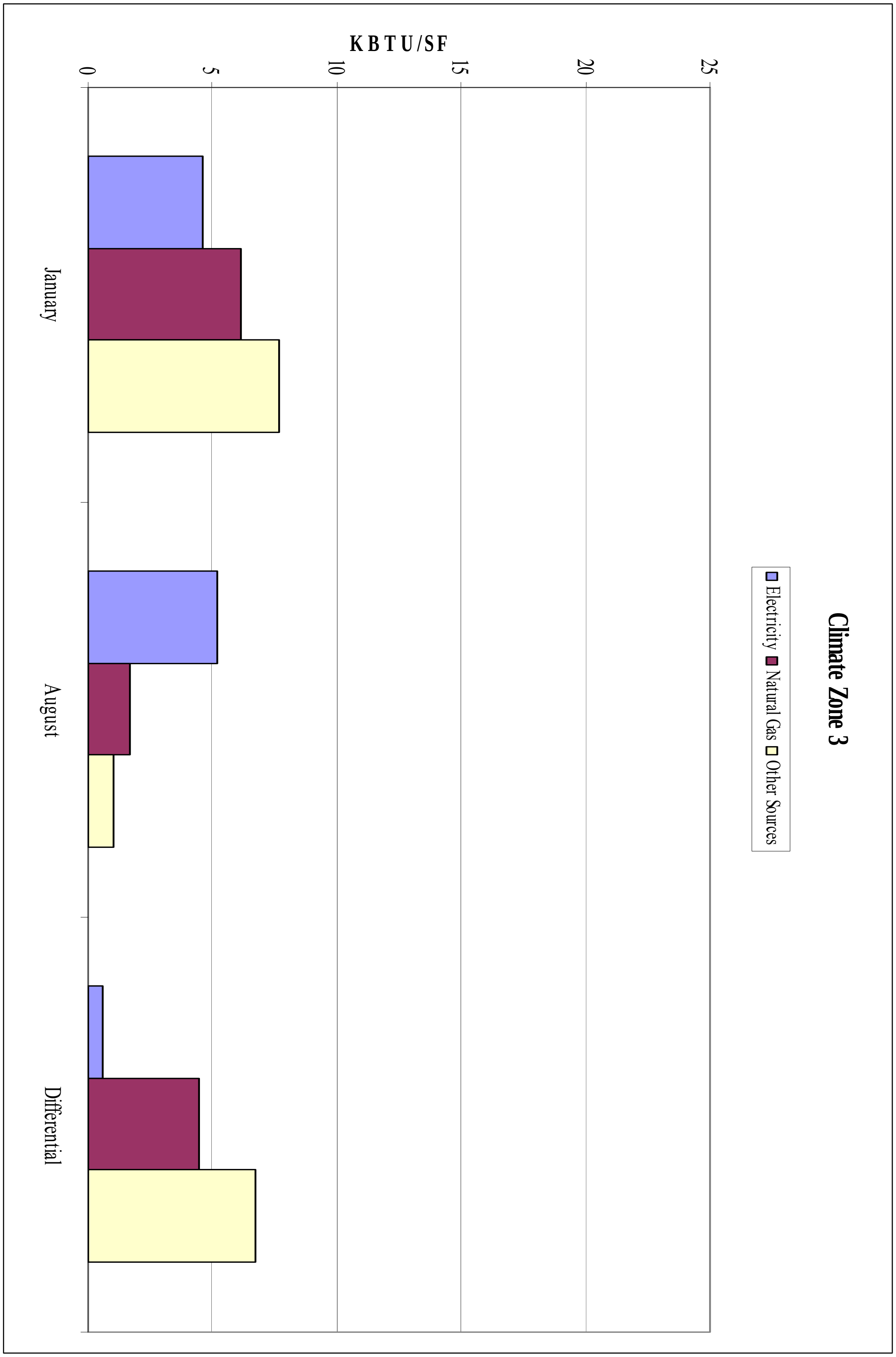
Electricity
Natural Gas
Other Sources
KBTU/SF
0
5
10
15
20
25
January
August
Differential


Climate Zone 2
Electricity
Natural Gas
Other Sources
KBTU/SF
0
5
10
15
20
25
January
August
Differential


Climate Zone 3
Electricity
Natural Gas
Other Sources
KBTU/SF
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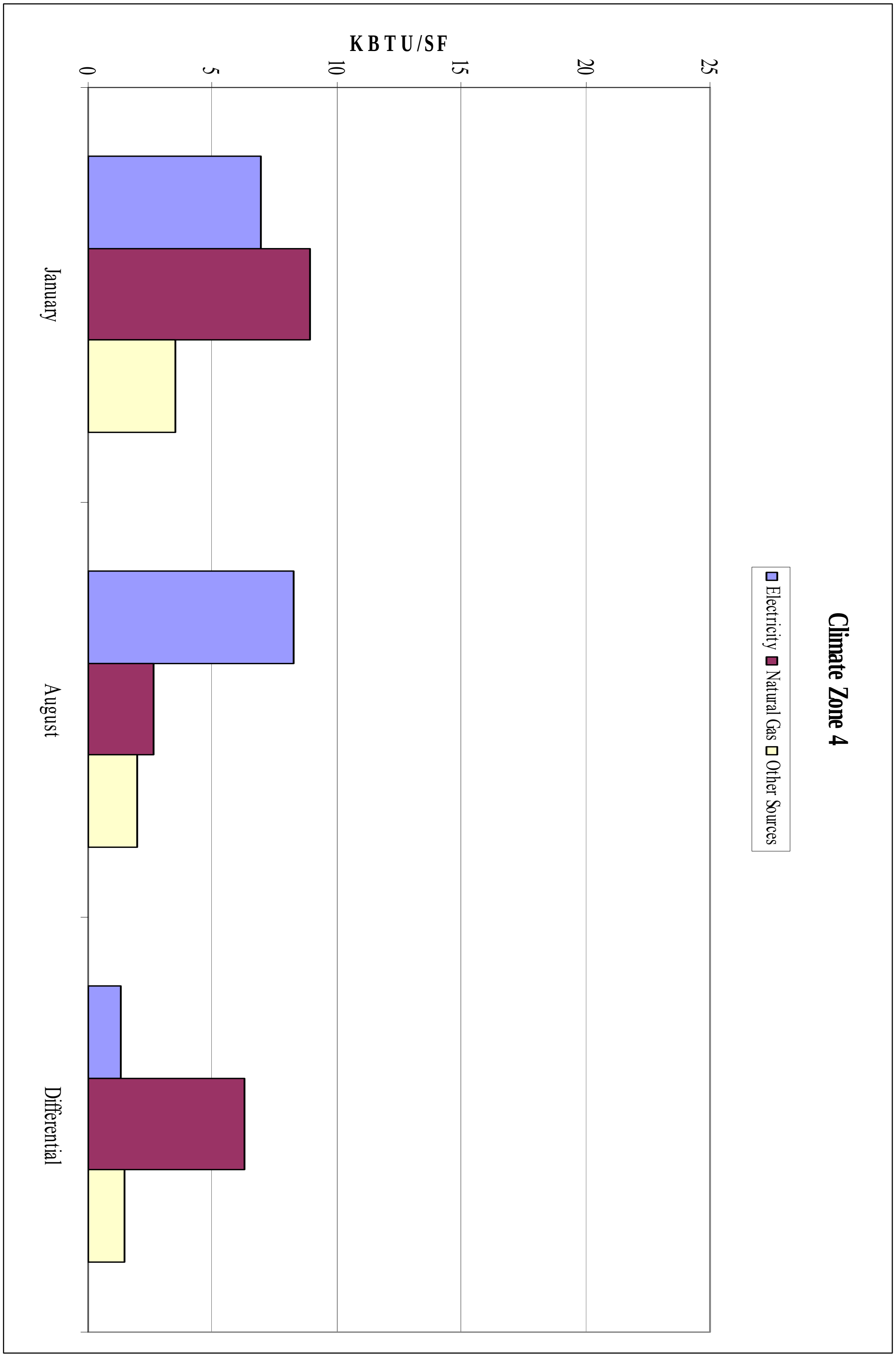
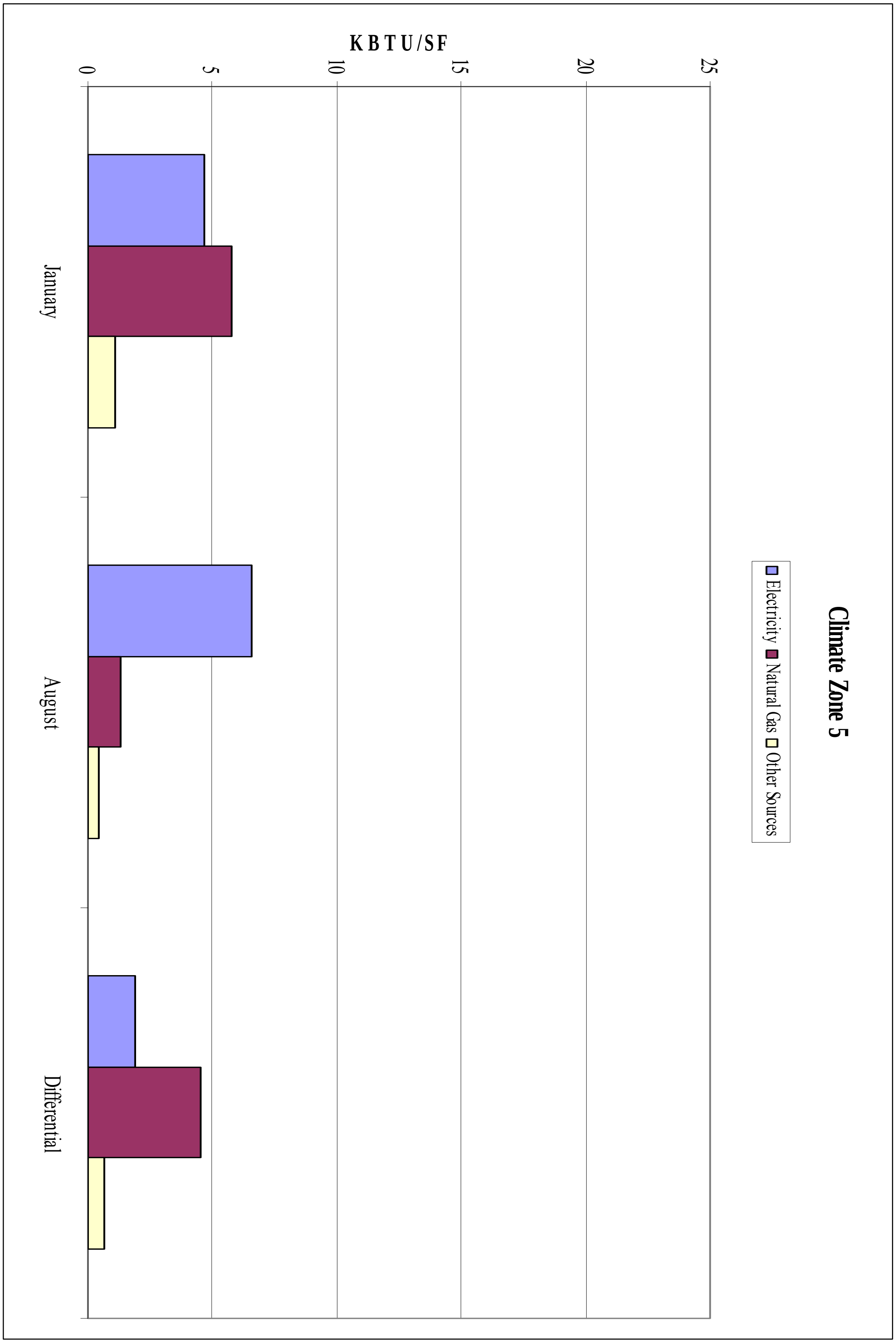
5
10
15
20
25
January
August
Differential



Climate Zone 4
Electricity
Natural Gas
Other Sources
KBTU/SF
0
5
10
15
20
25
January
August
Differential


Climate Zone 5
Electricity
Natural Gas
Other Sources
K B T U / S F
0
5
10
15
20
25
January
August
Differential

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Vita

Major James S. Griffin was born in Houston, Texas. He graduated from Katy High School, Katy, Texas, in 1989 and entered undergraduate studies at the United States Air Force Academy in Colorado Springs. He graduated with a Bachelor of Science degree in Engineering Mechanics in 1993 and received his commission on 2 June 1993. He was also awarded the degree of Masters of Business Administration from Louisiana Tech University in 1998. Major Griffin was assigned to Offutt AFB, Nebraska, Barksdale AFB, Louisiana, Misawa AB, Japan, Hickam AFB, Hawaii, and Seymour Johnson AFB, North Carolina. During these various assignments, he developed both depth and breadth of knowledge of the Civil Engineer career field, working base development, readiness, environmental, facility maintenance operations, and flight commander positions at base and Major Command levels.

Major Griffin was selected to pursue an advanced degree at the Graduate School of Engineering and Management, Air Force Institute of Technology, Air University at Wright Patterson AFB, Ohio in 2006. In 2008, he was selected to command the 386th Expeditionary Civil Engineer Squadron at Ali Al Salem AB, Kuwait.

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14. ABSTRACT

Energy consumption is a national concern, as evidenced by federal laws aimed toward facility energy conservation measures for federal organizations. Factors, primarily weather variables, that significantly impact energy consumption must be addressed and understood to align resources and programs to meet federal energy reduction goals. An energy model was created and tested to produce an appropriate forecasting tool for energy consumption. Energy demand at Air Force installations primarily depends on climatic conditions, with a small portion attributed to a base level of non-climatic conditions, such as interior lighting and appliance loads. By gathering all energy consumption and meteorological data covering 22 years for 74 Air Force installations throughout the world, an overarching predictive model was created. Specifically, heating degree-days, cooling degree-days, wind speed, and relative humidity data were collected and analyzed to determine the influence on energy consumption. The model showed a predictive value with adjusted R^2 above 81%. Additionally, trend analysis conducted over the 22-year period provided insight into the significant use of heating load requirements during the winter months as compared to cooling load requirements in summer months. This information should encourage energy policy makers to allocate more resources into heating system requirements than into cooling requirements, taking advantage of major opportunities to reduce energy consumption.

15. SUBJECT TERMS

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